# IT and Beyond: The Contribution of Heterogeneous Capital to Productivity

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Draft: March 2004

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**Abstract**

This paper explores the relationship between capital composition and productivity using a unique and remarkably detailed data set on firm-level investment in the U.S.. The 1998 Annual Capital Expenditure Survey (ACES) is the only available micro-level data set in the U.S. that provides information on investment spending across a wide range of detailed asset types. It provides a point-in-time snapshot of the investment composition decisions for a representative sample of roughly 30,000 firms spanning the entire U.S. private nonfarm economy. I first document a number of stylized facts about firm behavior in terms of disaggregate investment and capital mix. The primary focus of the paper, though, is analyzing the firm-level relationship between capital mix and productivity. By merging the investment data for the subset of publicly-traded firms with data on production inputs and output from Compustat, I am able to estimate the individual productivity contributions of various types of capital goods at the firm-level. The results indicate that several capital types, including (but not limited to) computers, communications equipment, and software, are associated with current and subsequent years' productivity. In fact, an analysis of firm fixed effects show that not only is productivity higher at firms that invest in certain capital goods but that productivity actually rises as a result of these investments. Moreover, I find investment in certain capital goods is also related to the growth in productivity, not just the level. [Keywords: Capital Heterogeneity, Productivity, Investment, Production Function Estimation; JEL Codes D21, D24, D29.]

# 1 Introduction

There has been a great deal of research in recent years regarding the relationship between investment in "high-tech" capital, most notably information and communications technologies (ICTs), and productivity. The macroeconomic literature has typically relied on growth accounting exercises to explore the issue, while microeconomic studies have generally approached the issue with firm- or establishment-level production function estimation, with ICT capital as a separate production input in addition to aggregate capital and labor. A consensus appears to be forming that ICT investment is associated with higher productivity, although the magnitude, direction of causality, and timing of this impact is still very much in debate.

Thus far, the productivity literature has focused nearly exclusively on ICT investment. The special focus on ICTs is natural given their increasingly ubiquitous application in business and personal life. However, there are several reasons to expand our attention beyond ICT's productivity impact to the impact of other capital goods as well, and in fact to expand our attention to the impact of the capital mix more generally. First, computers and communications equipment are not purchased in isolation. They are often purchased in conjunction with other capital goods to build a system of capital to accomplish productivity enhancements. This paper, in fact, provides evidence of exactly that. Thus, even if our interest is only in the productivity impact of ICT's, we must account for their correlation with other capital goods that have their own impact on productivity. Second, given that firm's have budget constraints, policy prescriptions calling for increased investment in ICT's are of little value without prescriptions as to what type(s) of capital should be replaced. For this purpose, one must know the productivity impacts of every type of capital. Third, though we are often compelled by model tractability and identification issues to assume perfect substitutability, different capital goods are clearly imperfect substitutes. It is thus important to assess the potential errors in inference that can occur by making this assumption. In other words, capital mix matters because of imperfect substitutability and it is important to know just how much capital mix matters in terms of determining productivity (e.g., total-factor productivity, as conventionally measured).

The goal of this paper is to begin to fill in this gap in the literature. Part of the cause of this gap has been a lack of micro data on investment across a wide range of capital goods. The recent Annual Capital Expenditures Survey (ACES) of 1998, however, fills this need. The 1998 ACES, conducted by the U.S. Census Bureau, is a unique data set reporting investment by 55 separate types of capital for over 30,000 U.S. companies spanning the private nonfarm economy.

Since little is known about firms' disaggregate investment behavior, the first part of this paper uses this data to document some firm-level, cross-sectional patterns regarding capital mix. First, I find substantial differences in investment composition across firms, even within narrowly-defined industries. Second, certain capital types (e.g., Computers, Software, Furniture, General Purpose Machinery) are shown to be used across a wide range of industries, suggesting generality of purpose.[1] Third, I find evidence that certain types of capital goods tend to be bundled, i.e., purchased in conjunction with each other. For instance, Computers tend to be purchased in conjunction with Software, Scientific Instruments, and Furniture, among other types. Fourth, it is shown that the typical firm tends to concentrate its capital expenditures in a small number of capital types. However, the types chosen vary from firm-to-firm.

The primary focus of the paper, though, is analyzing the firm-level relationship between capital mix and productivity. By matching a subset of the ACES companies to the Compustat research file (provided by Standard & Poors), I am able to observe firms' investment composition along with their quantities of factor inputs and output. Thus, I can explore the cross-sectional relationship between capital mix and productivity.

The results indicate that several capital types, including but not limited to computers, communications equipment, and software, are associated with current and subsequent years' productivity. These results are robust to measuring TFP directly using revenue shares or as the residual from a production function or labor productivity function. Taken at face value, the parameter estimates suggest that these capital goods have returns in excess of their "normal" returns given neoclassical predictions. Such excess returns could be the result of differential adjustment/learning-by-doing costs, unobserved co-investments (e.g., workplace practices), and/or expectational errors on the part of firms.

However, the relationship between capital mix and productivity is likely to be bidirectional. I attempt to disentangle the direct effect of capital mix on productivity from any reverse causality in a number of different ways. First, I follow an approach suggested by Olley and Pakes (1996), which uses a polynomial in current investment

[1] Throughout the paper, capital type names are capitalized to indicate that they refer to specific categories of capital listed in the Annual Capital Expenditures Survey.

and capital stock as a signal of the transmitted (to the firm's decisions) productivity component. My results turn out to be insensitive to the inclusion of this polynomial, suggesting that either the results are not driven by transmitted productivity shocks or that the Olley-Pakes approach is ineffective.

Second, I estimate the cross-sectional relationship between capital mix (in 1998) and productivity for each year in the 1995-2001 period. I then look at the time path of the estimated returns to investment for those capital goods for which I find *prima facie* evidence of excess returns. Though I do find evidence that productivity affects the investment composition decision, there is a clear shift in the point estimates of the investment composition-productivity relationship in the year of and the years after the investment composition decision. In particular, investment in communications equipment in 1998 has a much stronger association with productivity in 1999-2001 than it has with productivity in earlier years (including 1998).

The third approach to address the issue of causality is to make use of the panel data in Compustat to estimate firm fixed effects for both the pre-1998 and post-1998 period and then test whether investment in certain capital goods have a stronger relationship with the post-1998 fixed effects than they have with the pre-1998 fixed effects. I find the post-1998 relationship is considerably stronger – in particular, Computers and Communications Equipment. Relatedly, when I regress the *difference* between the post-1998 fixed effect and the pre-1998 fixed effect, which should measure a firm's productivity growth between the two periods, on the investment composition, I find that several capital goods, including Computers and Communications Equipment, are statistically and economically significant.

It should be noted that there is one important caveat to the results in this paper. Given that the 1998 ACES collected information on disaggregate investment and not disaggregate capital stocks and that the ACES for other years did not collect disaggregate data on either capital or investment, I must rely on the investment composition as a proxy for firms' capital composition. I show that this is likely to lead to a negative bias on the effect of any particular asset type (specifically, its share of total firm investment) on productivity. Thus, my results are likely to provide lower bounds on the productivity effects of each capital type.

The organization of the paper is as follows. The next section places this paper in the context of the economic literature. Section 3 describes the Annual Capital Expenditures Survey of 1998 and our matching of the ACES data to the Compustat research file. Section 4 explores a number of cross-sectional patterns that we find in the data relating to firm-level disaggregate investment behavior. The theoretical link between investment composition and productivity is discussed in Section 5. Section 6 presents the cross-sectional regression results, while section 7 provides the results of an analysis of firm fixed effects. Section 8 concludes.

# 2 Related Literature

As mentioned at the start of the paper, up to this point the literature on the productivity impact of disaggregate investment has focused almost exclusively on computers and communications equipment (and mostly just computers). During the 1980s and the first half of the 1990s, most studies found little or no evidence of an economically important contribution of ICT to productivity or productivity growth. Examples include Oliner and Sichel (1994), Griliches and Siegel (1992), and Berndt and Morrison (1995). More recently, a number of studies have found such a contribution. On the macroeconomic side, Oliner and Sichel (2000) used growth accounting techniques to identify the contribution, within a standard Neoclassical production framework, of ICT capital to aggregate productivity growth. They find that the use and production of ICT equipment together account for two-thirds of the acceleration in productivity growth that occurred between the first half and the second half of the 1990s.

Microeconomic studies have generally approached the issue with firm- or establishment-level production function estimation, with ICT-related capital (or investment) as a separate production input in addition to aggregate capital and labor. Greenan and Mairesse (2000) find evidence that computer utilization has a positive impact on productivity at the firm level using data on the French manufacturing and services sectors. However, they cannot reject the hypothesis that computer's contribution to productivity is the same as the contribution of other capital. Gilchrist, Gurbaxani, and Town (2003) use a modified version of the Arellano and Bond (1991) GMM estimator to estimate the elasticity of the IT capital stock via both a production function and a total factor productivity (TFP) framework. They find that IT's elasticity in the production function is about equal to its cost share and is not significant in the TFP regression (both consistent with the Neoclassical model). However, they also find that personal computers (PCs) have an impact on productivity above and beyond their contribution to the IT stock. They find this is driven by the durable goods sector; PCs have no impact in the nondurables sector. Brynjolfsson and Hitt (2003) estimate the elasticity of computers using both short- and long-difference regressions. They find that computers' elasticity is consistent with their cost share in the short differences; but, consistent with Gilchrist, *et al.*, the long difference results suggest that the elasticity is significantly higher than computers' cost share.

As discussed in Section 1, the productivity literature up to this point has generally focused exclusively on computers (and, to a lesser extent, communications equipment) in so far as it has explored disaggregate investment at all. The investment literature, however, has explored the implications of capital heterogeneity for adjustment costs (e.g., Chirinko (1993)) and tax policy (Goolsbee (2004)). Most relevant to this paper, Cummins & Dey (1998) found that adjustment costs for different capital types may be interrelated. This can mean that a particular capital good may have a higher return if it is bundled with other complementary capital goods. This result is consistent with the findings in this paper that certain bundles of capital goods are positively associated with productivity.

# 3 Data

## 3.1 1998 Annual Capital Expenditures Survey

The principal source of data for this paper is the 1998 Annual Capital Expenditures Survey (ACES).[2] The ACES is conducted annually by the U.S. Census Bureau to elicit information on capital expenditures by U.S. private, nonfarm companies. This information is used by the BEA in constructing the National Income and Product Accounts (NIPA).

In typical years, the ACES queries companies on their expenditures on total equipment and total structures, in addition to related values such as book value of capital assets, accumulated depreciation, retirements, etc.. In the 1998 survey, however, the ACES additionally required firms to report their investment broken down by 55 separate types of capital – 26 types of equipment and 29 types of structures. These data on disaggregate investment allow us to observe the complete composition of firms' investment, which is the focus of this paper. In fact, the survey requests

[2]For more details regarding the 1998 Annual Capital Expenditures Survey, including the published aggregate data and the actual survey questionaires, see Census Bureau (2000).

firms to break out their investment in this way separately for each of the industries in which they operate. Thus, the data is actually at the level of industry division *within* firms. In the following section, we present some summary statistics on investment composition at the firm-division level. However, since the focus of this paper is on the relationship between investment composition and productivity, and our data regarding productivity is at the firm-level, we aggregate the ACES investment data to the firm-level as well.

The 1998 ACES sampling frame consists of all U.S. private, nonfarm employers.[3] All companies with 500 or more employees were surveyed while smaller employers were surveyed based on a stratified random sampling such that larger firms were sampled with a higher probability. Response to the ACES is legally required so response rates are extremely high. The final sample consists of nearly 34,000 firms, of which approximately half have 500 or more employees.

The 1998 ACES is unique as the only large-scale micro-level U.S. survey of investment that disaggregates investment into a full range of detailed asset types (i.e., beyond simply total equipment and total structures, and beyond just one or two asset types such as computers or transportation equipment). These rich data on disaggregate investment provides us with a point-in-time snapshot of investment composition choices by a large number of firms spanning the U.S. private nonfarm economy. In the following section, we will analyze the cross-sectional patterns relating to investment composition. In sections 6 and 7, we explore the firm-level relationship between investment composition and productivity; to do so requires matching the ACES data with data on factor inputs and output.

## 3.2 Matching ACES to Compustat

Firm-level data on production inputs and output are available from the Compustat research file. Specifically, we obtained annual data on employment, total capital (book value), payroll (for a subset of firms), R&D expenses, and revenues, among numerous other items, for publicly-traded companies for 1992 through 2001.

A bridge file linking Compustat's unique firm identifier, CUSIP, with the unique firm identifier in the ACES was generously provided (and constructed) by Ron Jarmin

[3] In addition, a sample of companies with zero employees were sent an abbreviated questionaire which did not request the disaggregate investment detail.

and Kristen McCue of the Center for Economic Studies, U.S. Census Bureau. This bridge file allowed us to create a matched sample of roughly 3,000 firms that are included in both Compustat and ACES in 1998 (though about 1,000 of these firms had missing values for at least one of the variables needed for our productivity regressions). The majority of these matching firms were also present in Compustat in 1999-2001, allowing us to observe the relationship between investment composition and productivity in future years as well as the current year. Most of the matching firms are also included in Compustat in 1995-1997, which allows us to test for reverse causality.

One important aspect of the ACES investment data should be emphasized here before any data analysis. ACES provides data on *investment* by asset type, but not *capital stock* by asset type. One would prefer, of course, to have the latter given that theory suggests a relationship between *capital* composition and productivity, not *investment* composition (beyond its contribution to capital composition) and productivity. In the regression analysis in sections 6 and 7, we interpret the type-specific investment shares as proxies for type-specific capital shares. Investment shares are strictly proportional to capital shares only under very restrictive conditions. In Appendix B, I discuss the bias that obtains from using investment shares in lieu of capital shares. The discussion concludes that it likely results in a downward bias on the effect of a type's investment share on output and productivity, thus providing an lower bound on these effects.

# 4 Cross-Sectional Patterns of Firm-Level Investment Behavior

The full 1998 ACES sample provides us insight into disaggregate investment behavior. This section presents a number of summary statistics that reveal interesting and previously unexplored patterns in firm-level investment behavior.[4]

## 4.1 Average Composition

First, let us examine the average composition of investment in our sample. Table 1 shows the cross-firm, weighted mean of each asset type's share of firm investment.

[4]Unless otherwise indicated in the text, the summary statistics in this section are derived from the ACES data as aggregated to the firm-level rather than from the data at the firm-division level.

Observations are weighted by sample weight (inverse of sampling probability, adjusted for nonresponses) since small firms are undersampled in the ACES. There are 27,712 firms in the sample. The third column gives the asset type's mean share of firms' total investment while the fifth column gives the asset type's share of the subaggregate total equipment or total structures. Table 1 also shows, in columns 7 and 8, the number and percentage, respectively, of firms in the sample that have positive investment in that asset type. The asset types in the table are sorted by mean share of total investment.

Computers are nearly one-third of total capital expenditures for the average firm. This average share is much higher than that of any other capital good. The next highest share is for Autos, which, on average, comprise about one-eighth of firm investment. Other capital goods that make up at least 5% of the average firm's total investment are Furniture (7.9%); Office Buildings (7.7%); Other Office Equipment (6.2%); Plants (5.2%); and General Purpose Machinery (5.0%).

It should be noted that a small average investment share could arise either from a large number of firms having a small investment share or from a small number of firms having a large investment share (while the rest of firms are near zero). The latter tends to be the case for structures while the former tends to the case for equipment types. For example, "Other Commercial Stores/Buildings, NEC" averages a relatively high 4.5% of total investment (9th most out of the 55 types) even though less than 2% of the sample invested in this type of structure. In contrast, 13.6% of the sample purchased software but software accounted for less than 1% of the average firm's investment.[5]

## 4.2 Identifying Range of Use

By decomposing the total (cross-firm) variance in a capital good's investment share into its within-industry and between-industry components, we can assess the range of use of the capital good. This is somewhat related to the concept of a general purpose technology (GPT), which is a technology that facilitates a wide range of productive

[5] The ACES software category consists only of software that is capitalized (for accounting purposes) and purchased separately from hardware. The fact that this kind of software, on average, comprises a very small share of firms' investment even though a considerable percentage of firms purchase it may be partially because firms purchase this kind of software in conjunction with other kinds of software (including expensed software). Hence, the average investment share for Capitalized Software Purchased Separately is likely well below the average share for total software, while our measured percentage of firms investing in this kind of software is probably near that for total software.

activities, rather than a narrow set of activities. A capital good that embodies a new technology and is found to be used in a wide range of industries may well be considered a GPT.

The $R^2$ from regressing a capital type's investment share on the full set of 3-digit SIC industry dummies measures the between-industry share of the total cross-firm variance in the investment share. Table 2 displays these $R^2$'s for each asset type. A low $R^2$ indicates that the capital type's investment share varies little from industry to industry (relative to its overall variance) – in other words, the capital type is used across a wide range of industries (to the extent it is used at all). The types of equipment found to have the widest range of use are generally those one would intuitively expect to be general purpose: Computers, Other Office Equipment, Software, Fabricated Metal Products, General Purpose Machinery, Autos, and Furniture. This provides statistical support for the common impression that computers and software are GPT's. Perhaps less intuitive, we also find Metalworking Machinery and Medical Equipment to have widespread use. Structures, as one might expect, generally have much higher $R^2$'s then equipment, reflecting the more specialized functions that structures have. Exceptions are Medical Offices (consistent with the low $R^2$ for Medical Equipment), Religious Buildings, and Transportation Facilities.

## 4.3 Analysis of Cross-Sectional Variance

Recall that the ACES data is actually collected at the level of industry divisions within the firm. Thus, an interesting question that can be answered with this micro data is: how much of the variance in an asset type's share of investment is due to differences across divisions within a firm as opposed to differences across firms? To answer this question, I do the following for each asset type: First, I compute the asset type's share of investment for each firm-division. I then compute each firm's mean of the investment share across divisions within the firm and subtract it from the firm's division-level investment shares. Lastly, I compute the total sample variance of these demeaned investment shares, which gives us the within-firm variance, and divide it by the total sample variance of the non-demeaned firm-division-level investment shares. The resulting ratio tells us what fraction of the total variance in the asset type's investment share is within-firm versus between-firm. I perform this exercise both conditioning on firms having multiple divisions and unconditionally.

It turns out that very little of the total firm-division-level variance in a capital type's investment share (for any capital type) is within-firm. Conditional on firms having multiple divisions, the ratio of within-firm to total variance ranges across asset types from 0.01 to 0.39. For equipment, the median (and mean) ratio is 0.27; for structures, the median ratio is 0.26 (mean is 0.22). The unconditional ratios are much lower (median is 0.12 for equipment and 0.13 for structures). Thus, a substantial majority of the variance in investment shares is between-firm, suggesting that establishments/divisions within firms tend to be fairly homogenous in terms of their capital composition. This implies that the firm-level is likely sufficiently disaggregate for studying the link between productivity and capital composition.

## 4.4 Bundling of investment: The Case of Computers

Capital goods are not used in isolation. They are often used together as part of a capital infrastructure system. This should be especially true for GPT's such as computers. Table 3 provides evidence of what capital types tend to be purchased in conjunction, or instead of, computers. Specifically, for each capital type, we calculate the partial correlation between the computer investment share and that type's investment share, controlling for 3-digit industry effects. Table 3 provides the weighted correlations for those types that have a statistically significant partial correlation with computers. Observations are weighted by sample weight (unweighted correlations, not shown, are very similar). Among equipment, Computers tend to be purchased in conjunction with Other Office Equipment; Scientific Instruments; Software; Aerospace Products; Furniture; and Artwork, Books, & Other Equipment, NEC. Capital goods that generally are purchased separately from Computers are Communications Equipment; Metalworking Machinery; Special Industry Machinery; Cars and Light Trucks; Heavy-Duty Trucks; Engine, Turbine, and Power Transmission Equipment; Electrical and Distribution Equipment; Mining and Oil & Gas Field Machinery; and Miscellaneous Equipment. Among structures, Computers are most often purchased with Office, Bank, & Professional Buildings; Multi-Retail Stores; and Other Commercial Buildings/Stores, NEC. On the other hand, firms with capital expenditures on the following types of structures tend not to purchase Computers in the same year: Industrial Nonbuilding Structures; Automotive Facilities; Air, Land, & Water Transportation Facilities; Telecommunications Facilities; Electric, Nuclear, & Other Power Facilities; Petroleum & Natural Gas Wells; and Other Mining & Well Construction.

## 4.5 Lumpiness of Investment along the type dimension

It is well documented that investment is extremely lumpy over time at the microeconomic level (see, e.g., Doms and Dunne (1998)). However, we know little about the microeconomic lumpiness, or concentration, of investment over capital types. The question is: in a given year, do firms tend to invest only in a small number of capital types or do they spread their investment dollars across a wide range of types?

To answer this question, for each firm I calculated the number of asset types in which the firm reported positive investment. Figures 1a and 1b show the cross-sectional distribution of this number across the firms in our sample. Figure 1a gives the distribution for equipment; Figure 1b gives the distribution for structures. Of the 21,686 firms that reported positive equipment investment, a little less than 30% of investing firms reportedly purchased only one type of equipment. 16% reported investment in two types, 15% in three types, 12% in four types, and 9% in five types. The frequencies decline with the number of reported types (though, for non-disclosure purposes, the tail of the distribution is truncated at 18-23 types). The average equipment-purchasing firm reported investment in 3.4 types of equipment.

As expected, investment in structures tends to be highly concentrated. In fact, 72% of the 10,782 firms that reported positive structures investment invested in just one type of structure. 16% reported investing in two types, almost 7% reported investing in three types, and the frequencies continue to decline thereafter with the number of types. The average number of structure types that firms invested in (conditional on having positive structures investment) was 1.5.

The low number of types that most firms report investing in, especially for structures, in part may reflect inaccuracy on the part of respondents. That is, decomposing their firm's capital expenditures into a large number of disaggregate asset types may impose an exorbitant time and record-keeping burden on respondents. It is difficult to determine with certainty whether respondents truncate the number of asset types for which they report investment, but it may contribute to measurement error in the investment shares.

Nonetheless, the fact that 72% of firms report investment in only a single structure type, combined with the fact (established in Table 1) that no single structure type comprises more than a quarter of the average firm's investment in structures, suggests that firms tend to concentrate construction investment on a single type of structure but that this type differs from firm to firm. The particular type of investment a firm chooses appears to be primarily determined by the industry to which the firm belongs, as evidenced by the high $R^2$'s in Table 2. Thus, in the regressions below, the investment shares for structures types may indeed pick up industry effects beyond the 3-digit SIC level (we control for 3-digit industry effects with 3-digit industry dummies). The coefficients on structure type's investment shares therefore should not be interpreted necessarily as reflecting the productivity contributions of investment in these types.

# 5 The Relationship between Productivity and Investment Composition

The primary focus of this paper is on the relationship between capital mix and productivity. In the typical Neoclassical production framework, once aggregate capital is accounted for, capital mix plays no role in determining output. Consider the standard Cobb-Douglas production function in capital and labor with a Hicks-neutral technology shift parameter (the usual subscripts for time and economic unit are omitted for expositional purposes): $Y = AK^{\alpha}L^{\beta}$. Assuming the necessary and sufficient conditions for the existence of a single aggregate $K$ hold (see Solow (1955) and Fisher (1965)), $K$ can be considered the sum of disaggregate (real) capital stocks – stocks differentiated either by type or by vintage (here by type).[6] The (ex-post) production function can then be written as follows:

$$\begin{aligned} Y &= A\left[K + \theta_1 K_1 + ... + \theta_P K_P\right]^{\alpha} L^{\beta} \\ &= A\left[1 + \theta_1 \xi_1 + ... + \theta_P \xi_P\right]^{\alpha} K^{\alpha} L^{\beta} \end{aligned} \tag{1}$$

[6] Solow (1955) established that a necessary and sufficient condition for the existence of a single capital aggregate is that the marginal rate of substitution between different capital types is independent of the quantity of labor (i.e., the heterogeneous capital types must be weakly separable). In addition, Fisher (1965) demonstrated that if different types (or vintages) of capital embody different levels of quality/technology, then there is an additional necessary and sufficient condition for the existence of a single capital aggregate: the heterogeneous quality must be expressible in homogenous constant-quality units – this is the well-known "better = more" assumption. Taken together, these two conditions are equivalent to requiring that different capital types be perfect substitutes once they are properly expressed in constant-quality units. For the majority of the paper, I assume these conditions hold although I do not make the further assumption that ex-post marginal products per dollar of investment are equal across capital subaggregates.

where $K = \sum_{p=0}^{P} K_p$ and $\xi_p = K_p/K$; $p$ indexes capital types: $p = 0, 1, ..., P$.

Each $K_p$ is measured in physical units, or equivalently, (nominal) dollars. The weights, $\theta_p$, convert the dollar value of capital of type $p$ to quality units that can be compared across types; the quality of $K_0$ is used as the numeraire. $K$ is the total dollar value of capital.

The real marginal products of $K_p$ and $K$, respectively, are:

$$\begin{aligned}\frac{\partial Y}{\partial K_p} &= \frac{\alpha Y\,(1+\theta_p)}{[K+\theta_1 K_1 + ... + \theta_P K_P]} \\ \frac{\partial Y}{\partial K} &= \frac{\alpha Y}{[K+\theta_1 K_1 + ... + \theta_P K_P]},\end{aligned}$$

and hence the capital type $p$'s relative marginal product is:

$$\frac{\partial Y}{\partial K_p} / \frac{\partial Y}{\partial K} = 1 + \theta_p.$$

Thus, $\theta_p$ represents the percentage difference between capital type $p$'s marginal product and the aggregate marginal product of capital (or equivalently, capital type $p$'s relative ex-post rate of return). A finding of $\theta_p \neq 0$ for some type $p$ is thus a rejection of the hypothesis of normal (Neoclassical) returns to capital type $p$. In terms of the production model, the $\theta_p$'s can be thought of as a reduced-form representation of factors that could cause realized (ex-post) marginal products to differ across capital goods. Such excess (or below-normal) returns could be the result of adjustment costs and/or learning-by-doing, unobserved organizational co-investments, or expectational errors by firms (regarding the true marginal product of an investment).

If $\sum_{p=1} \theta_p \xi_p \approx 0$, then we can use the approximation $\log(1+x) \approx 0$ if x is small and obtain the following production function in logs (lowercase letters denote logs)[7]:

$$y = a + \alpha\,[\theta_1 \xi_1 + ... + \theta_P \xi_P] + \alpha k + \beta \ell \tag{2}$$

[7] Any approximation error introduced here is likely to result in a negative bias in OLS estimation of the $\theta_p$s. For simplicity, consider the case where there is only one capital type ($p = 1$) in addition to the numeraire type. As $\theta_1 \xi_1$ diverges from zero, the approximation error, $\log(1 + \theta_1 \xi_1) - \theta_1 \xi_1$, which is an omitted variable in the estimation, will become increasingly negative. So if the true $\theta_1$ is nonzero, then the omitted variable will be more negative for firms with larger shares of investment in type 1 ($\xi_1$). Hence, there will be a negative bias on the estimator of $\theta_1$. In particular, notice that any findings of excess returns that we obtain are likely to be underestimates whereas findings of below-normal returns may be overstated.

The principal focus of following section is on obtaining consistent estimates of the sequence of $\theta_p$s ($\{\theta_p\}_{p=1}^{P}$), i.e., the coefficients on the investment shares. At least three regression specifications allowing for the estimation of $\{\theta_p\}$ can be derived from (2). First, adding an i.i.d. disturbance term, equation (2) forms a regression equation from which one can estimate the parameters $a$, $\alpha$, $\beta$, and $\{\theta_p\}$. Second, the production function specification can be converted into a labor productivity specification by subtracting $\ell$ from both sides of (2).[8] Third, assuming constant returns to scale and perfect competition, we can measure $\alpha$ and $\beta$ using capital and labor's income shares, respectively, and subtract $(\alpha k + \beta \ell)$ from both sides of (2) in order to obtain a multi-factor productivity (MFP) specification:

$$mfp = a + \alpha \left[\theta_1 \xi_1 + ... + \theta_P \xi_P\right] + \epsilon$$

where $\epsilon$ is an i.i.d. disturbance term.

The shift variable $a = \log(A)$ is an unobserved variable that is likely to vary by firm and may possibly be correlated with the other regressors. To formalize this possibility let us rewrite $a$ as: $a_{it} = f_i + \omega_{it} + \upsilon_{it}$. The first term is a firm fixed effect. The second term is a productivity shock that is known to the firm when it makes its input decisions but is unobserved to the econometrician. The third term is the productivity innovation that is *ex-ante* unknown even to the firm. It is this third term that we are after: the relationship between the capital mix and $\upsilon_{it}$ represents the causal effect that capital mix has on productivity. The concern regarding the regressions described above is that both $f_i$ and $\omega_{it}$ may be correlated with firm's investment decisions, including the capital composition decision, leading the OLS estimators of our parameters to be biased. As for the fixed effect, $f_i$, ordinarily one could control for this through panel data methods (e.g., first-differencing). In this paper, however, I have only a single cross-section of data (1998) on $\{\xi_p\}$, though I do have panel data for the variables $y$, $k$, and $\ell$ (below we discuss an alternative exercise which makes use of this panel data, though not to identify $\{\theta_p\}$). Due to this limitation of the data, our primary identification strategy is to focus on the cross-sectional estimation and include as many potential correlates with unobserved contributors to productivity (i.e., with $f_i$ and $\omega_{it}$) as possible.

First, we include a number of variables measuring permanent firm character-

[8] In the labor productivity regressions for which I report results below, I assume constant returns to scale so that labor can be excluded as a regressor.

istics. These consist of 3-digit SIC level industry dummy variables, state dummies, and a 5-category indicator of firm size (employment); this size variable is described in Appendix A. Second, we include a dummy variable indicating whether or not the firm had an investment spike (defined as investment 20% or more of the beginning-of-year book value of capital). Third, Olley and Pakes (1996) demonstrated that under certain conditions, the unobserved productivity shock may be proxied by a polynomial function of (total) investment, capital, and age. That is, $\omega_{it} = g(I_{it}, k_{it}, age_{it})$. Though we do not observe firms' age, we do observe total investment and total capital stock (book value), so we include a third-order polynomial of $I$ and $k$ (including cross-terms) in addition to the other regressors.

It should be noted, however, that other studies have shown that the Olley-Pakes conditions may frequently be violated in practice.[9] Thus, we discuss two sets of results: one set which does not include such a polynomial and one set that does.

One issue that must be clarified before proceeding is the appropriate measure of output ($Y$). Typically, one assumes that real value added is produced using capital and labor, as in $Y = AK^{\alpha}L^{\beta}$. However, properly measuring real value added can be quite difficult, especially at the micro level. The most common measure is double-deflated value added, which is deflated gross output ($\approx$sales) minus deflated materials. Separate deflators for materials costs are generally unavailable. Moreover, even if they were, double-deflated value added has been shown to be a biased measure of real value added in the presence of imperfect competition (see Basu & Fernald (1996)).

In light of these problems with value added as a measure of output, I opt instead to use gross output. Since gross output is theoretically a function of materials, as well as capital and labor, one must decide on how materials enter into the production function. One option is to have materials as an additional factor in the Cobb-Douglas production function: $Y = AK^{\alpha}L^{\beta}M^{1-\alpha-\beta}$ (assuming constant returns to scale). In practice, though, materials tend to be dominate the explanatory power of capital and labor in micro level estimation, making it difficult to identify the coefficients on capital and labor. Another option is to assume that value added ($AK^{\alpha}L^{\beta}$) and materials have a Leontief relationship and therefore materials can be excluded from the gross output production function (this is the approach most often followed in the micro production estimation literature). I follow the latter approach for the most part in this paper. However, for the MFP regressions, I report results using both a two-factor ($K$ and

[9] See, e.g., [1].

$L$) productivity (2FP) measure and a three-factor ($K$, $L$, and $M$) productivity (3FP) measure. Furthermore, as an additional robustness check, I also report 2FP results based on using double-deflated value added instead of gross output.

# 6 Results of cross-sectional regressions

As mentioned in Section 3, the 1998 ACES covers 55 types of capital assets. At this level of type-disaggregation, investment in most types of capital was reported to be zero for a high percentage of firms. Therefore, for the purpose of the regressions, we joined some types together to create a new, 20-type classification system in order to reduce the frequency of zeros in the investment shares, and hence increase their cross-sectional variability. The mapping from the original 55 ACES categories to the 20 categories we use in the regressions is shown in Table 4.

In the description below of the regression results, the focus is generally on the "general purpose" capital goods: Computers, Communications Equipment, Software, Instruments, Fabricated Metal Products, etc.. Other asset categories, particularly structures, are predominately industry-specific asset types. Their inclusion in these regressions serves more to control for industry effects not accounted for by the 3-digit SIC industry dummies.

## 6.1 Production Function Regressions

Tables 5-8 present the main results of the cross-sectional regressions (described above in Section 5. Table 5 presents the estimates of the parameters in equation 2. In parentheses, robust standard errors are shown (robust to heteroskedasticity). The first column of results pertains to a regression containing only 1998 variables. Results in the second column are from a regression where all variables, except the investment shares (which are only available in 1998), are 1999 values. The third and fourth columns refer to regressions for 2000 and 2001, respectively. All of these regressions include dummy variables controlling for 3-digit industry, state of the firm's headquarters, the employment size class of the firm, and whether the firm engaged in an investment spike in 1998. The coefficients on the industry and state dummies are not disclosed to avoid confidentiality concerns.

We include the investment spike dummy because firms with an investment spike may incur high adjustment costs in 1998 and subsequent years which will be reflected in lower output and productivity than they otherwise would obtain. Conversely, the spike may reflect the firm's response to a positive productivity shock. Either way, it should be included in our regressions since investment spikes may consist disproportionately of certain capital goods, thus excluding the spike variable could bias the coefficients on the investment shares of those capital goods.

First, I discuss the results of regressions that do **not** include a polynomial in current (total) investment and capital stock as is called for in Olley and Pakes (1996) as a way to control for unobserved productivity shocks transmitted to the firm's input decisions. Results for such regressions are discussed below in Section 6.4.

Computers, communications equipment, and software are statistically significantly associated, usually above the 99% level, with higher productivity (i.e., output controlling for capital and labor) for all four years in our sample, 1998-2001. The computer coefficient is generally around 0.5, suggesting that an increase in the computer investment share by 10 percentage points (and corresponding decrease in investment share for special industry machinery, the numeraire capital type ($K_0$), which is the omitted category in the regressions) would be expected to be associated with 5% higher output, which, since we're controlling for capital and labor, implies 5% higher multi-factor productivity. At their peak, software and communications equipment have even larger effects.

Some other types of capital also have significant coefficients. Offices are positively and significantly (at above the 99% level) associated with productivity for all four years in our sample. Aircraft have a negative and significant (at the 95% level) coefficient in 2000. Lastly, General Purpose Machinery has a positive and significant (95%) coefficient in 2001.

I estimate the elasticity of output with respect to labor to be .49-.53 and the elasticity of output with respect to capital to be .41-.44. These estimates are reasonable, though the estimates of labor's elasticity are somewhat below that implied by factor shares while capital's elasticity estimates are somewhat above.

The coefficient on the spike variable is positive and significant for 1998 and 1999. Its value implies that a spike is associated with 7-8% higher output in the current and following year. The effect becomes smaller and insignificant in subsequent years. Firm size, as proxied by employment size, has no significant relationship with productivity in these regression, all else equal (which is not surprising given that $\log(L)$ is already included in the regression).

The estimated coefficients on the investment shares represent estimates of $\alpha\theta_p$s. One can convert the share coefficients back to the $\theta_p$s by dividing them by the estimated capital elasticity ($\approx .4$). Take, for instance, our main production function estimates for 1999. The coefficient estimate on computer's investment share is 0.57 and the estimated capital elasticity is 0.43. These estimates thus imply that the ex-post rate of return on computers in 1998 was 133% greater than the return on aggregate (average) capital. Our estimates imply that the relative return on communications equipment was 188%, that of software was 177%, and that of office buildings was 114%.

## 6.2 Labor productivity regressions

Overall, the results from the labor productivity regressions are nearly identical to those from the production function regressions discussed above. As in the production function regressions, Computers, Communications Equipment, and Software are statistically significantly associated, usually at the 99% level, with higher productivity for all four years in our sample, 1998-2001. The coefficient values and the time path of coefficients on these types is also similar to above. Also as in the production function regressions, Offices are positively and significantly (at above the 99% level) associated with labor productivity for all four years in our sample, while Aircraft investment is negative and significant (at the 95% level) in 2000 and General Purpose Machinery is positive and significant (95%) in 2001.

The coefficient on the capital-labor ratio implies an elasticity of output with respect to capital of .40 to .45, which is reasonable though perhaps slightly higher than expectations. The spike variable is found to have the same effect on labor productivity as it was found to have on output: a spike is associated with 7-8% higher labor productivity in the current and following year, with the coefficient becoming smaller and insignificant in subsequent years.

Above we found no effect of firm size on output. In contrast, labor productivity generally declines with firm size, as evidenced by the increasingly negative coefficients on the firm size dummies as the size category increases.

## 6.3 Multi-Factor Productivity Regressions

As discussed in Section 5, one can also estimate the set of parameters $\{\theta_p\}$ using a multi-factor productivity specification. One can include materials $(M)$ in addition to $K$ and $L$ to obtain a measure of 3FP or one can exclude materials to obtain a measure of 2FP. When we use 2FP or 3FP as the dependent variable and regress it on the investment shares, the precision of the estimates of the investment share coefficients is reduced (relative to the production function or labor productivity specifications), especially for 3FP. It appears that the measures of MFP, which rely on observed factor shares, contain a good deal of noise. This is not surprising given that labor expenses had to be imputed for the majority of firms due to frequent nonreporting of labor expenses in Compustat. Nonetheless, the results with 2FP or 3FP as the dependent variable are broadly consistent with those from the production function or labor productivity regressions.

As in the previous regressions, when the dependent variable is 2FP, evidence is found of a positive and significant relationship between investment and multi-factor productivity for Computers, Communications Equipment, Software, and Offices. These relationships are found in all four years, with the exception of Communications Equipment in 1998 and Computers in 2001 (in both cases, the estimated coefficient has a p-value just over 10%).

Though the results are roughly similar, the precision of our estimates is reduced considerably when we replace 2FP with 3FP as the dependent variable, suggesting that the measurement error in 3FP is worse than that in 2FP. In the 3FP regressions, the coefficient on Computers remains positive and significant in 1999 but no longer is so in 1998. Communications Equipment is now only significant (and only at the 90% level) in 2000. Similarly, Software is significant (at the 90% level) only in 1999. Fabricated Metal Products and Metalworking Machinery have positive and significant coefficients in 1998 and 1999, and General Purpose Machinery also has a positive and significant coefficient in 1999.

## 6.4 Robustness checks

As mentioned in Section 5, a common concern in production function estimation is simultaneity bias, which could arise if there is an unobserved productivity component that simultaneously affects the input decisions and the output realization. This is of particular concern in cross-sectional regressions since one cannot difference-out even non-time-varying unobserved productivity components. One technique to address simultaneity bias is that proposed by Olley and Pakes (1996). They show that under certain conditions, the productivity shock may be proxied by a polynomial consisting of current investment, capital stock, and age (and their cross-terms). Thus, as a robustness check on our results, we add a 3rd-order polynomial of total investment and capital stock (we do not observe age), and their cross-terms, as additional regressors in each of the above regressions. We find this addition has virtually no effect on the results, though the output elasticities with respect to labor and capital do move closer to their factor shares but only slightly.

In the 2FP results discussed above, gross output was used as the measure of output in the construction of 2FP. Using gross output as the output measure in a two-factor ($K$ and $L$) production framework assumes that value added and materials are weakly separable in the production function. An alternative approach which does not require this assumption is to use double-deflated value added as the output measure in the construction of 2FP. The drawbacks of this approach are that (1) we lack separate deflators for gross output and materials to use in the double deflation, and (2) the double-deflated value added measure may be biased under imperfect competition (Basu & Fernald (1996)).

When we use this alternative measure of 2FP, we find similar results to those discussed above, though the estimates are less precise. Computers have a positive and significant coefficient for 1998 (at 90% level) and 1999 (at 95% level), and then become insignificant in 2000 and 2001. Communications Equipment has no significant relationship with 2FP in 1998 but has a positive and significant (at 99% level) relationship in 1999 and 2000. Instruments are positively and significantly related to 2FP in 1998 (at 95% level, and marginally in 2000, at 90% level). The coefficients on capital types Fabricated Metal Products and Metalworking Machinery are positive and significant in 1998 (at the 95% and 90% levels, respectively) and 1999 (both at the 99% level). Lastly, General Purpose Machinery has a positive and significant relationship with 2FP in 1999 (95% level).

Another alternative way to measure 2FP in this paper is to use the reported sales collected in ACES rather than that collected in Compustat. Obviously, since the ACES data cover only 1998, we can only construct this ACES version of 2FP (gross output) for 1998. If we use the ACES version of 2FP in our 1998 regression (full specification), again Computers are found to have a positive and highly significant (above 99% level) relationship with 2FP. This regression also yields positive and significant coefficients on Communication Equipment and Cars & Light Trucks.

In sum, our various alternative regressions are virtually unanimous in finding a positive and statistically significant relationship between Computer's share of investment and productivity. This is true for productivity in the current year and at least the subsequent three years, though the effect appears to be strongest for productivity one year out. Communications Equipment and Software are found to have a significant positive relationship with productivity in the majority of our regressions, but the statistical significance of their coefficient is sensitive to the choice of dependent variable. Other capital types are occasionally found to be significantly related to productivity, but for none of these is the relationship particularly robust. Interestingly, the capital types for which we find evidence of a significant link to productivity tend to be those identified as having a wide industry usage in Table 2.

The results discussed above demonstrate that capital composition, at least with respect to certain capital types, is significantly related to productivity. But how important is composition in explaining the cross-sectional variation in productivity? This question can be answered by looking at the $R^2$'s of the regressions including investment shares compared with the $R^2$'s of the same regressions excluding the shares. Consider the labor productivity regressions (similar results obtain from the other specifications): The $R^2$'s for the labor productivity regressions, including all dummy variables, are between .64 and .67, depending on year; the $R^2$ for the 1999 regression is .643. To find out how much of the cross-sectional variation in labor productivity is explained by the investment shares, we re-run the 1999 regression excluding the investment shares. The $R^2$ falls to .598. Thus, an additional 4.5% of the variance in labor productivity can be explained by investment shares above and beyond what can be explained by the aggregate capital stock alone.

## 6.5 Manufacturing vs. Nonmanufacturing

It is conceivable that certain capital goods would have different ex-post rates of return in manufacturing than in nonmanufacturing. Since the same capital good may be used for different purposes in manufacturing than in nonmanufacturing, there could be differences between the two sectors in the degree of adjustment costs, the organizational co-investments, and errors in expectations as to the return from investment in the capital good. Therefore, an interesting extension of the regressions discussed above is to estimate them separately for manufacturing and nonmanufacturing. Tables 10 and 11 shows the results of this extension.

Table 10 gives the coefficient estimates and robust standard errors from estimating the production function specification in Eq. (2) for the manufacturing sector. Table 11 gives the analogous results for nonmanufacturing. As before, the regressions are estimated using annual cross-sections for 1998-2001; again, for all cross-sections, the investment shares are measured in 1998. Also as before, these regressions include 3-digit industry dummies, state dummies, the investment spike dummy, and the employment size class indicator.

In manufacturing, Computers have a positive and significant relationship with productivity in 1998, but the point estimate is relatively small (0.28) and the estimates in subsequent years are near zero and insignificant. In nonmanufacturing, the Computer investment share is significant in 1998 and 1999 (at the 90% level). Moreover, its estimated coefficient is considerably larger in nonmanufacturing for all four years (though the difference is not statistically significant).

Communications Equipment appear to have positive excess returns in both sectors, at least after the initial year of investment (1998) (though the statistical significance of Communications Equipment is slightly greater in nonmanufacturing). Software's investment share has a positive and significant (above the 95% level) relationship with productivity in manufacturing in all four years. In nonmanufacturing, the estimated coefficient on software is large and highly significant in 1998, but it is insignificant in subsequent years. Part of this insignificance is due to less precision (higher standard errors) in the estimator of this coefficient in nonmanufacturing, but it may also reflect higher excess returns on software in manufacturing than in nonmanufacturing.

General Purpose Machinery is another type of equipment for which there are noticeable differences between the two sectors. In manufacturing, the General Purpose Machinery investment share is positive and significant (at 90% level or above) in each of the years 1999-2001. In nonmanufacturing, it is insignificant in all years. Though it is likely that excess returns on General Purpose Machinery are indeed higher in the manufacturing sector, the results may also reflect that few nonmanufacturers invest in this type of equipment – therefore, there is less variance in its investment share in nonmanufacturing and hence its coefficient can be less precisely estimated (which is consistent with the fact that the point estimates between manufacturing and nonmanufacturing are not much different, but the nonmanufacturing standard errors are larger).

The biggest difference between manufacturing and nonmanufacturing, though, appears to be in the returns to Instruments. In manufacturing, though Instruments are statistically significant only in 1998 (and only at the 90% level), the point estimates are positive and relatively large ($\approx$ 0.2 to 0.4). In contrast, the point estimates on Instruments in nonmanufacturing are highly negative ($\approx$ -0.3 to -0.9) – statistically significantly so in 2000 and 2001. This could be because the kinds of instrument used in nonmanufacturing are actually different than those used in manufacturing (e.g., medical instruments instead of scientific/measuring instruments), and different kinds of instruments have had different rates of return. Alternatively, it may suggest that for any given type of Instrument, manufacturers received higher returns (or, equivalently, under-invested) than nonmanufacturing firms.

As for types of structures, I find that Offices, Commercial Buildings, Utility Structures, and Other Structures all have much higher relative rates of return for manufacturing firms than for nonmanufacturing firms. Since these are categories of structures not typically associated with manufacturing, a high investment share in one of them by a manufacturing firm may reflect that the firm is highly diversified. Therefore, the higher returns to these structures in manufacturing may reflect that diversified firms have higher productivity than non-diversified firms, whereas in nonmanufacturing, ownership of these structures does not indicate industrial diversity/scope.

## 6.6 Dynamics of Relative Rates of Return

The path that the estimated coefficient on a capital type takes over time may reflect the length of the adjustment process (e.g., learning-by-doing) associated with that capital type. Furthermore, in addition to the regressions for 1999-2001, one can estimate regressions for years prior to the investment composition decision. This allows one to assess whether the estimated relationship between capital mix and productivity is greater after the capital mix decision or before. The answer to this helps us determine which direction of causality dominates. Therefore, I estimate the cross-sectional production function regressions discussed above for 1995-1997, in addition to the 1998-2001 regressions.

Figure 2 shows the estimated coefficients for three particularly interesting capital goods: Computers, Communications Equipment, and Software. First, note that the estimated coefficient for Communications Equipment is clearly higher after 1998 than before 1998, suggesting that the predominant direction of causality is from the investment decision to productivity. For software and computers, the estimates prior to 1998 are not much different from their values after 1998.

Next, consider the time path of the coefficients from 1998 onward. These paths may reflect the adjustment process involved with each capital type. The coefficient on Communications Equipment peaks in 1999 and then stays near that level at least through 2001. Software, on the other hand, peaks in 1998, suggesting that software may require less of an adjustment process.

Recall from Section 5 that coefficients on different capital types can differ from each other for various reasons: differences in adjustment costs and/or the learning-by-doing process, differences in unobserved organizational co-investments, or differences in expectational errors by firms (regarding the true marginal product of an investment in a particular capital good). These factors may also explain the differences in the time paths of different capital goods. For instance, the fact that Communications Equipment's coefficient rises after the investment decision, and stays high at least three years out, may indicate that the investment immediately increases productivity and then, due to slow learning or adjustment, it continues to benefit productivity for a number of years. It could also be that communications equipment investment is one part of wider productivity-enhancing changes in organizational structure and workplace practices, which have long-lasting effects on firm productivity. Lastly, it could simply be that communications equipment really does have an independent and lasting contribution to productivity in excess of the contribution from other capital, but that firms did not realize this *ex-ante* when making investment decision (otherwise, they would have purchased more communications equipment, driving down its marginal product).

# 7 Relationship between Capital Mix and Firm Fixed Effects

Despite our efforts to control for unobserved productivity differences across firms with the inclusion of variables likely to be correlated with the unobserved fixed productivity component, it is impossible to fully account for the potential effect of firm fixed effects with cross-sectional data. As mentioned above, though, we do have panel data for all of the variables in our model except the investment shares. Hence, it is possible to estimate firm fixed effects using the Compustat data, though obviously these fixed effects will not be orthogonal to capital mix.

These fixed effects should contain useful information. Consider estimating cross-sectional regressions of the form in equation 2 but without the investment shares. One can estimate such a cross-sectional regression separately for a number of years. The estimated residuals can be averaged over those years to obtain an estimate of the firm fixed effects. This averaging has the advantage of removing some of the year-to-year noise in the data. The fixed effects, then, should capture slow-moving and/or permanent firm factors that affect productivity (as measured). These factors include unobserved labor quality, workplace practices (e.g., human-resource management practices), co-investments, and other so-called "intangible capital." Lev and Radhakrishnan (2003), in fact, measure intangible capital in exactly this way, as the fixed effect from a production function estimation using Compustat data. Thus, an interesting question is whether these fixed effects are related to the capital mix and how. Furthermore, does capital mix have a greater relationship with the post-1998 fixed effect than it does with the pre-1998 effect, suggesting a causal link from capital mix to productivity? Finally, does capital mix affect the difference between the post-1998 and pre-1998 effects, suggesting a causal link from capital mix to productivity *growth*?

To answer these questions, first we estimate two sets of fixed effects, one for a period just before the 1998 observed investment mix decisions are made, 1995-97, and one for a period just after, 1999-2001. To estimate a period's fixed effect, we obtain the residuals, for each year, from the cross-sectional production function regression described above (equation 2), including the polynomial in $I$ and $k$ (so the residual should be orthogonal to $\omega_{it}$, assuming the Olley-Pakes conditions hold). We then regress each of these period's fixed effects on the 1998 investment shares.[10] If the

[10] Black and Lynch (2001) follow a similar approach to evaluating the impact of workplace practices on productivity, given a single year's data on workplace practices: First, they estimate a standard production function using establishment-level panel data and using the within or GMM estimator to account for the transmitted unobserved productivity component ($\omega_{it}$ in our model). They then average the residuals over the period 1987-93 to obtain establishment fixed effects. Lastly, they regress these fixed effects on firm-level measures of workplace practices (including human capital investments

permanent factors in intangible capital affect firms' capital mix decisions, then we should find statistically significant nonzero coefficients on investment shares in both of these two regressions. This finding would suggest that permanent factors have an effect on capital mix, though this does not preclude the possibility that capital mix has a causal effect on productivity as well. On the other hand, if we find that the investment shares are significantly larger in the latter period's regression, then it must be the case that the capital mix does indeed have a causal effect on productivity.

In order to address the question of whether capital mix affects productivity *growth*, we compute the difference between the post-1998 effect and the pre-1998 effect and regress it on the investment shares. A finding of a significantly positive (negative) coefficient on a capital type's investment share suggests that investment in that capital type caused productivity to increase (decrease) more than it would have otherwise.

## 7.1 Results

### 7.1.1 Productivity levels

The results of these regressions are shown in Table 9. The first column of coefficient estimates are from a regression of the pre-1998 (1995-1997) fixed effect on each of the investment shares. As in the earlier regressions, Special Industry Machinery is the omitted category. A number of capital types have a statistically significant relationship with the pre-1998 fixed effect.

The fact that investment in 1998 in these types of capital are significantly related to productivity fixed effects in the pre-1998 period suggests that intangible capital (i.e., the slow-moving and permanent productivity factors captured by the fixed effects) does affect the investment composition decision. Not surprisingly, firms with high levels of intangible capital tend to subsequently invest in Computers, Software, Communications Equipment, and Offices – capital typically associated with innovative workplace practices, high labor quality, etc.. Such firms also appear to invest relatively more in General Purpose Machinery and Industrial Buildings.

The second column of estimates in Table 9 shows the results from regressing the post-1998 (1999-2001) fixed effect on the investment shares. Most of the same capital

and computer usage) from a 1994 survey. My approach is an extension of this technique in that I perform the analysis for both a pre-survey period and a post-survey period in order to identify the direction of causality between the survey variables and productivity.

types that were found to be associated with pre-1998 average productivity are found to be associated (in the same direction) with post-1998 average productivity. This suggests that there is an important permanent component in these fixed effects that is related to capital mix.

Comparing the pre-1998 results with the post-1998 results, notice that the post-1998 coefficients are greater for a number of capital types. In particular, Communications Equipment has a substantially greater coefficient in the post-1998 period than in the pre-1998 period. This suggests that, even though intangible capital/permanent productivity factors have an effect on the capital mix decision, capital mix, particularly the share of capital in communications equipment, has a *causal* effect on productivity. In other words, these results suggest that investment in communications equipment *raises* productivity.

#### 7.1.2 Productivity growth

So capital mix appears to affect the level of a firm's productivity. But does capital mix affect productivity *growth*? To answer this question, we regress the difference between the post-1998 effect and the pre-1998 fixed effects on the investment shares. This difference represents the (percentage) jump in productivity between the pre-1998 period and the post-1998 period. The estimated coefficients on the investment shares are shown in the last column of Table 9.

I find that, as was the case regarding the average productivity levels, both Computers and Communications Equipment are positively and significantly related to the growth in productivity between the two periods. Autos, Commercial Buildings, Utility Structures, and Other Structures are also positively and significantly related to productivity growth. Offices, on the other hand, are found to be negatively and significantly related to productivity growth.

This OLS regression of the difference in fixed effects on investment shares cannot control for the possibility of reverse causality. For instance, it is possible that there was some omitted dynamic factor that affected productivity growth between the pre-1998 and post-1998 periods and simultaneously affected the capital mix (e.g., a new CEO hired in 1998). Nonetheless, it seems likely that at least part of the effect of capital mix on productivity growth is causal.

# 8 Conclusion

This paper has shown that, for a number of capital goods, including ICT capital, investment is associated with higher productivity. Moreover, by analyzing measures of firm fixed effects, I found evidence that investment in certain capital goods leads to subsequent increases in productivity. These results support the growing consensus that ICT's have had a positive impact on total-factor productivity in recent years. They also show that this conclusion is robust to controlling for other simultaneous capital investments.

Given the purely cross-sectional nature of the disaggregate investment data from the 1998 ACES, however, it is impossible to fully disentangle the effect of investment/capital mix on productivity from possible feedback in the opposite direction. Plans for (some) future ACES surveys call for such disaggregate investment detail to be collected again, which may allow future research to better address this issue (as well as other issues).

As for this paper, it is still a work in progress. Ongoing research is being done on a couple of fronts. First, I am exploring whether bundling of capital co-investments (e.g., computers + software) have an added effect on productivity. This means adding interactions between capital types' investment shares into the regressions discussed above. Thus far, it appears that many such interactions are significantly associated with productivity. Second, I am investigating whether R&D spending is complementary (or substitutable) with investment in any particular capital goods. The one limitation here is that R&D is frequently unreported by firms in the Compustat data set.

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# 10 Appendix A – Variable construction

The following is a list of the key variables used in this paper and how they were constructed from the data at hand:

**Real Output** – Real Output is obtained by dividing Compustat's sales variable (SALES_NET) by the BEA's 3-digit SIC level gross output deflator (P): Y = SALES_NET/P.

**Total capital** – Total capital (K) is obtained by deflating Compustat's Property, Plant, and Equipment (Total - Gross) (PPEGT) by the BLS's 2-digit total investment deflators. Following Brynjolfsson and Hitt (2003), the deflator is applied at the calculated average age of capital, based on a 3-year (t, t-1, t-2) average of the ratio of total accumulated depreciation (ACC_DEPR) to current depreciation (Depreciation and Amortization: DP). ACC_DEPR is calculated as Property, Plant, and Equipment (Total - Gross) minus Property, Plant & Equipment (Total - Net): ACC_DEPR = PPEGT - PPENT.

**Labor** – The labor input (L) is measured as the number of employees (EMP) reported in Compustat.

**Wages** and **Labor Costs** – For a subset of firms, Compustat provides data on Labor and Related Expenses (XLR). For these firms, the average wage can be obtained by dividing XLR by EMP. For firms with missing values for XLR, I impute the average wage by multiplying the firm's number of employees (EMP) by the 3-digit industry mean of average wages, computed over firms with nonmissing values for XLR. If there 2 or fewer firms with nonmissing XLR in that 3-digit industry, I use the 2-digit industry mean. XLR for firms with missing values is then imputed by taking the product of the imputed average wage and the reported value of EMP.

**Nominal Materials Costs** – Nominal materials (PM) are calculated (using Compustat) as sales net of Operating Income Before Depreciation (OIDBP) and Labor and Related Expenses (XLR):

PM = SALES_NET - OIDBP - XLR.

An equivalent definition is Cost of Goods Sold (COGS) plus Selling, General, and Administrative Expense (XSGA) minus XLR:

PM = COGS + XSGA - wL.

The two definitions are equivalent since OIDBP is defined as SALES_NET-COGS-XSGA. I use the first definition unless it yields a missing value in which case I use the second definition.

**Real Materials Costs** – Real materials costs (M) are calculated as nominal materials (PM) deflated by the BEA's 3-digit gross output deflator (P). Unfortunately, no separate deflator exists that is specific to materials.

**2-factor productivity** – The natural log of 2-factor productivity (2FP), which is the dependent variable in the 2FP regressions, is computed using the following formula:

$$2FP = y - \left(\frac{rK}{PY}\right) k - \left(\frac{wL}{PY}\right) \ell$$

where $y$, $k$, and $\ell$ are the logs of real output (Y), total capital (K), and labor (L) (all defined above). $r$ is the capital rental price, obtained at the 2-digit SIC level from the BLS. $wL$ comes from Compustat's variable, Labor and Related Expenses (XLR).

As discussed in Section 5, as a robustness check, I also use an alternative measure of 2FP where Y is replaced by double-deflated value added (VA): VA = Y - M.

**3-factor productivity** – Similar to $2FP$, the natural log of 3-factor productivity (3FP) is computed as:

$$3FP = y - \left(\frac{rK}{PY}\right) k - \left(\frac{wL}{PY}\right) \ell - \left(\frac{PM}{PY}\right) m$$

where $y$, $k$, $\ell$ and $m$ are the natural logs of output, capital, labor, and materials, respectively.

**Investment Spike** – The investment spike dummy variable (SPIKE) is 1 if current total investment is equal to or greater than 20% of K; 0 otherwise.

**Employment Size** – The employment size class indicator (SIZE) can take on five values:

SIZE = 1 if L $<$ 1000

SIZE = 2 if 1000 $\leq$ L $<$ 2000

SIZE = 3 if 2000 $\leq$ L $<$ 4500

SIZE = 4 if 4500 $\leq$ L $<$ 11500

SIZE = 5 if 11500 $\leq$ L

# 11 Appendix B – Potential bias from using investment mix instead of capital mix

As mentioned in the introduction to the paper, there may be bias in our estimates due to using investment shares instead of capital shares. Here I explore the likely magnitude and direction of that bias.

Note that from the standard perpetual inventory equations, $I_{pt}^i = \triangle K_{pt}^i + \delta_p K_{p,t-1}^i$ and $I_t^i = \triangle K_t^i + \delta K_{t-1}^i$, we get:

$$\frac{I_{pt}^i}{I_t^i} = \frac{(g_{pt}^i + \delta_p)}{(g_t^i + \delta)} \cdot \frac{K_{p,t-1}^i}{K_{t-1}^i}$$

For type $p$'s investment share to be proportional to its capital share, one needs firms' type-$p$ capital shares to be stable from year to year (i.e., $K_{p,t-1}^i / K_{t-1}^i = K_{pt}^i / K_t^i$), and that $g_{pt}^i$ and $g_t^i$ be the same for all firms. Lehr and Lichtenberg (1999) also faced the problem of how to interpret firm-level data on investment shares given an absence of data on capital shares. They assumed a steady state where $g_{pt}^i = g_t^i = 0$ and

$K^i_{p,t-1}/K^i_{t-1} = K^i_{pt}/K^i_t$, which makes investment shares a multiple – constant over firms and years – of capital shares. The stability of the capital share between any two years seems reasonable, but the restriction that all firms grow at the same rate (be it zero or something else) is clearly unrealistic.

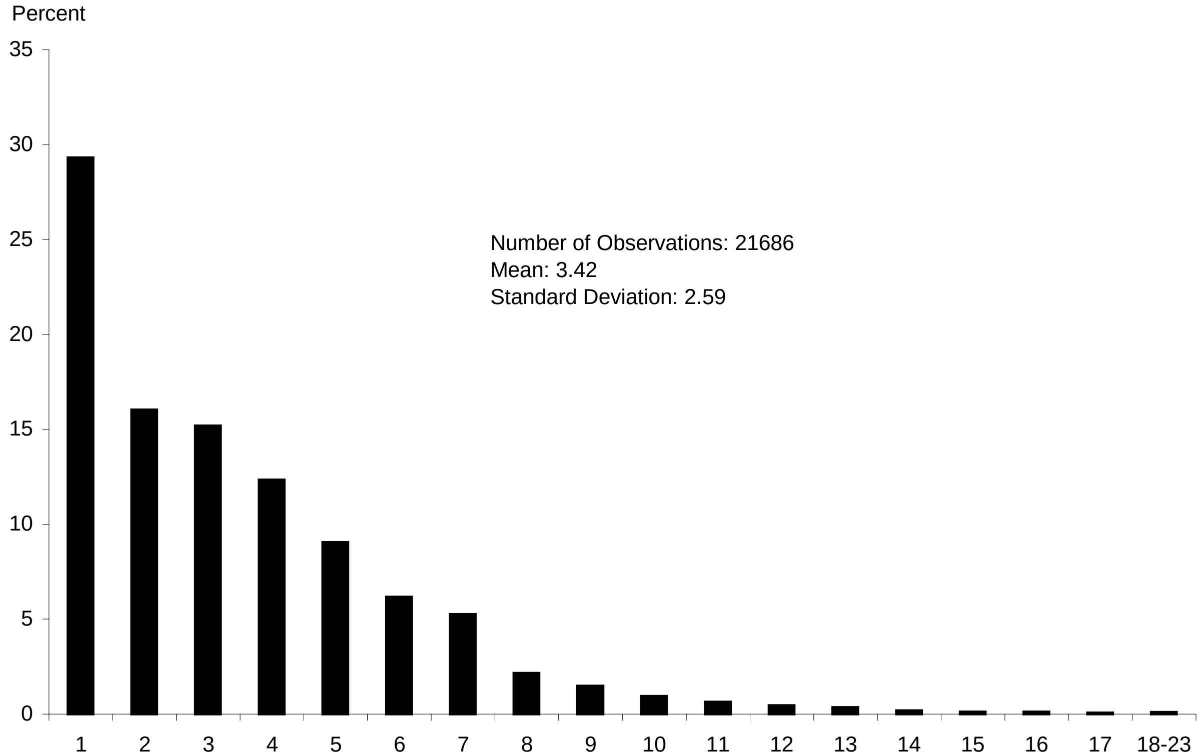
Using $I^i_p/I^i$ as a substitute for $K^i_p/K^i$ in the regressions above results in the following omitted variable:

$$M = \frac{I^i_p}{I^i}\left[\frac{(g^i+\delta)}{(g^i_p+\delta_p)} - 1\right]$$

The direction of the bias on the coefficients on $I^i_p/I^i$ depends on the (partial) correlation between $I^i_p/I^i$ and $M$ (controlling for other included regressors), which depends on the partial correlation between $I^i_p/I^i$ and the term in brackets. The term in brackets is the percentage difference between the total-capital investment rate $(I^i_t/K^i_{t-1})$ and the type-$p$ investment rate $(I^i_{p,t}/K^i_{p,t-1})$. Since type-specific investment is likely to be lumpy over time, i.e., higher than normal (conditional on industry and other regressors) type-$p$ investment this year generally implies lower than normal beginning-of-year type-$p$ capital stock, firms that have higher type-$p$ investment shares tend to be those with higher relative investment rates for type-$p$ capital (inverse of the term in brackets). Thus, the partial correlation between $I^i_p/I^i$ and the omitted variable is most likely negative, which implies a negative bias on the estimator of the investment share's coefficient $(\alpha\theta_p)$. In particular, significantly positive estimates of $\alpha\theta_p$, such as those we obtain for Computers, Software, and Communications Equipment, cannot be explained by omitted variable bias.

Figure 1

**A. Distribution of number of equipment types for which a firm has non-zero investment**




**B. Distribution of number of structure types for which a firm has non-zero investment**

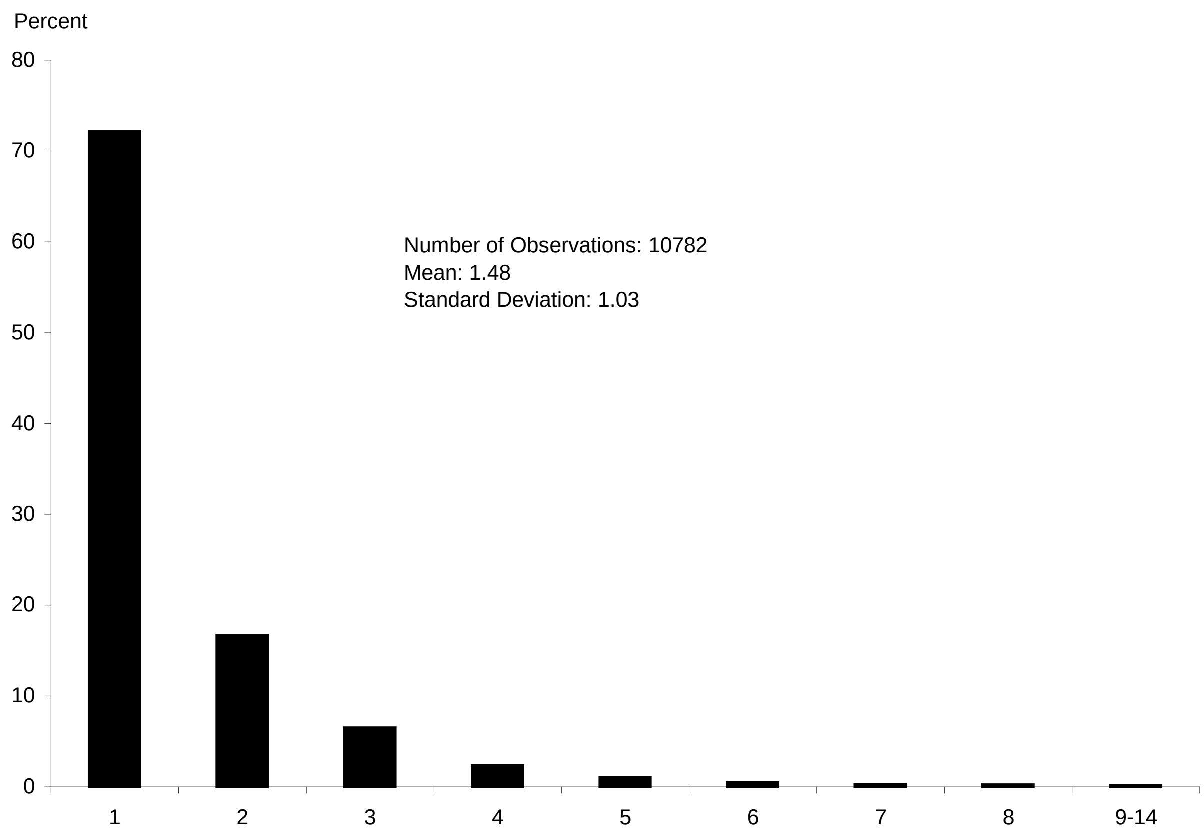


**Figure 2. Time Path of Labor Productivity Regression Coefficients**

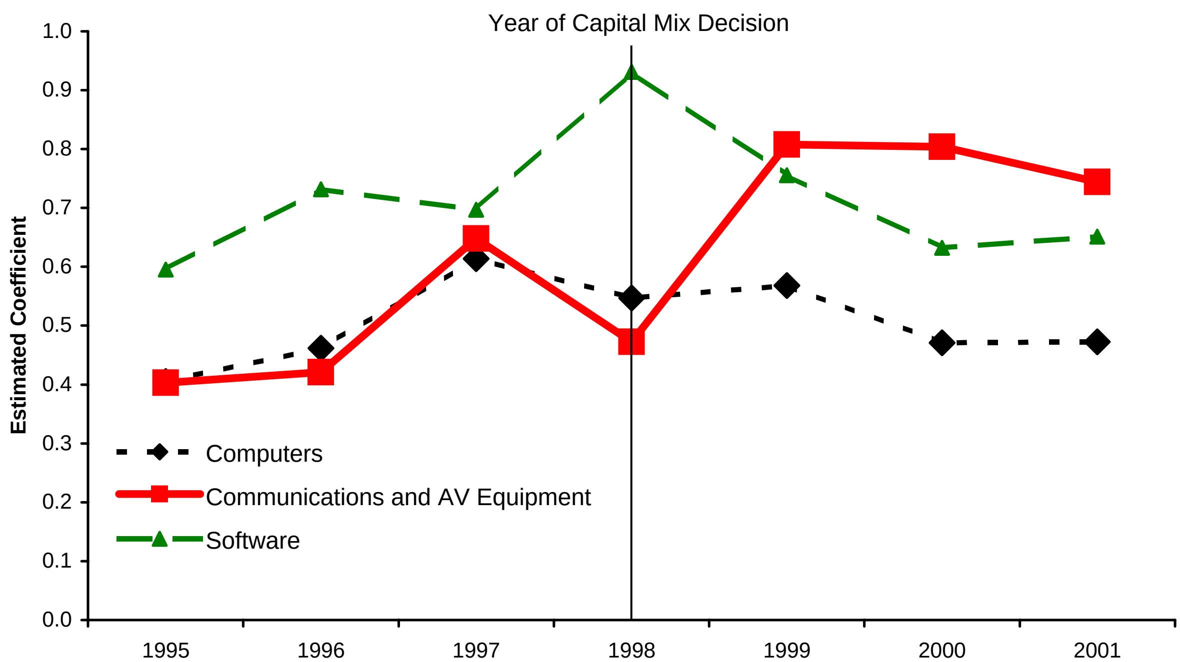


**Table 1. Mean investment share and # of firms with positive investment, by capital type**

| Type | Description | Total Investment Share | | Equipment (or Structures) Investment Share | | # of firms with positive investment | % of sample with positive investment |
|---|---|---|---|---|---|---|---|
| | | Weighted Mean | Std. Deviation | Weighted Mean | Std. Deviation | | |
| 311 | Computer and Peripheral Equipment | 0.320 | 0.416 | 0.324 | 0.418 | 15362 | 55.4% |
| 331 | Cars and Light Trucks | 0.126 | 0.303 | 0.128 | 0.304 | 6621 | 23.9% |
| 351 | Furniture and Related Products | 0.079 | 0.235 | 0.082 | 0.238 | 8562 | 30.9% |
| 141 | Office, Bank, and Professional Buildings | 0.077 | 0.184 | 0.243 | 0.418 | 4175 | 15.1% |
| 312 | Office Equipment Except Computers and Peripherals | 0.062 | 0.209 | 0.063 | 0.210 | 6736 | 24.3% |
| 131 | Manufacturing, Processing, and Assembly Plants | 0.052 | 0.174 | 0.163 | 0.358 | 3403 | 12.3% |
| 324 | General Purpose Machinery[1] | 0.051 | 0.196 | 0.052 | 0.198 | 4347 | 15.7% |
| 152 | Stores - Food Related | 0.048 | 0.167 | 0.108 | 0.308 | 858 | 3.1% |
| 155 | Other Commercial Stores/Buildings, NEC | 0.045 | 0.166 | 0.093 | 0.287 | 487 | 1.8% |
| 323 | Special Industrial Machinery | 0.045 | 0.190 | 0.045 | 0.192 | 4467 | 16.1% |
| 315 | Medical Equipment and Supplies | 0.042 | 0.192 | 0.043 | 0.193 | 2211 | 8.0% |
| 313 | Communications, Audio, and Video Equipment | 0.036 | 0.154 | 0.037 | 0.157 | 5867 | 21.2% |
| 334 | Other Transportation Equipment | 0.030 | 0.155 | 0.030 | 0.156 | 2160 | 7.8% |
| 354 | Service Industry Equipment | 0.030 | 0.162 | 0.031 | 0.165 | 1620 | 5.8% |
| 154 | Warehouses and Distribution Centers (except Passenger) | 0.027 | 0.118 | 0.074 | 0.249 | 1205 | 4.3% |
| 111 | Residential Structures | 0.027 | 0.139 | 0.038 | 0.182 | 382 | 1.4% |
| 332 | Heavy Duty Trucks | 0.026 | 0.148 | 0.026 | 0.148 | 1573 | 5.7% |
| 353 | Construction Machinery | 0.026 | 0.151 | 0.026 | 0.151 | 977 | 3.5% |
| 322 | Metalworking Machinery | 0.024 | 0.144 | 0.024 | 0.145 | 1700 | 6.1% |
| 151 | Automotive Facilities | 0.024 | 0.122 | 0.051 | 0.218 | 333 | 1.2% |
| 162 | Special Care Facilities | 0.023 | 0.117 | 0.039 | 0.185 | 653 | 2.4% |
| 171 | Amusement and Recreational Facilities | 0.018 | 0.102 | 0.027 | 0.144 | 301 | 1.1% |
| 355 | Other Miscellaneous Equipment | 0.018 | 0.122 | 0.018 | 0.125 | 1458 | 5.3% |
| 361 | Artwork, Books, and Other Equipment, NEC | 0.017 | 0.118 | 0.018 | 0.119 | 1614 | 5.8% |
| 201 | Preschool, Primary/Secondary, and Higher Education Facilities | 0.017 | 0.113 | 0.022 | 0.143 | 214 | 0.8% |
| 352 | Agricultural Equipment | 0.014 | 0.110 | 0.014 | 0.111 | 552 | 2.0% |
| 121 | Hotels, Motels, and Inns | 0.012 | 0.096 | 0.016 | 0.125 | 214 | 0.8% |
| 153 | Multi-Retail Stores | 0.010 | 0.075 | 0.025 | 0.151 | 503 | 1.8% |
| 343 | Electrical Equipment, NEC | 0.010 | 0.095 | 0.010 | 0.095 | 844 | 3.0% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **TABLE 1 continued…** | | | | | | | |
| 321 | Fabricated Metal Products | 0.008 | 0.082 | 0.008 | 0.082 | 1070 | 3.9% |
| 316 | Capitalized Software Purchased Separately | 0.008 | 0.063 | 0.008 | 0.064 | 3768 | 13.6% |
| 314 | Navigational, Measuring, Electromedical, and Control Instruments | 0.008 | 0.077 | 0.008 | 0.077 | 1072 | 3.9% |
| 192 | Electric, Nuclear, and Other Power Facilities | 0.007 | 0.072 | 0.009 | 0.094 | 296 | 1.1% |
| 223 | Other Non-building Structures, NEC | 0.006 | 0.059 | 0.018 | 0.122 | 484 | 1.7% |
| 161 | Hospitals | 0.006 | 0.055 | 0.013 | 0.109 | 736 | 2.7% |
| 191 | Telecommunication Facilities | 0.005 | 0.057 | 0.014 | 0.116 | 160 | 0.6% |
| 112 | Manufactured (Mobile) Homes | 0.005 | 0.058 | 0.007 | 0.070 | 21 | 0.1% |
| 142 | Medical Offices | 0.005 | 0.048 | 0.018 | 0.130 | 505 | 1.8% |
| 202 | Special School and Other Educational Facilities | 0.003 | 0.046 | 0.004 | 0.062 | 84 | 0.3% |
| 181 | Air, Land, and Water Transportation Facilities | 0.002 | 0.034 | 0.007 | 0.079 | 339 | 1.2% |
| 344 | Mining and Oil and Gas Field Machinery and Equipment | 0.002 | 0.044 | 0.002 | 0.045 | 346 | 1.2% |
| 212 | Petroleum and Natural Gas Wells | 0.002 | 0.033 | 0.002 | 0.048 | 81 | 0.3% |
| 342 | Electrical Transmission and Distribution Equipment | 0.001 | 0.026 | 0.001 | 0.027 | 545 | 2.0% |
| 222 | Highway and Street Structures | 0.001 | 0.024 | 0.002 | 0.045 | 121 | 0.4% |
| 193 | Water Supply, Sewage, and Waste Disposal Facilities | 0.001 | 0.024 | 0.002 | 0.035 | 163 | 0.6% |
| 333 | Aerospace Products and Parts | 0.001 | 0.026 | 0.001 | 0.026 | 412 | 1.5% |
| 213 | Other Mining and Well Construction | 0.001 | 0.022 | 0.001 | 0.034 | 62 | 0.2% |
| 341 | Engine, Turbine, and Power Transmission Equipment | 0.001 | 0.021 | 0.001 | 0.021 | 251 | 0.9% |
| 132 | Industrial Nonbuilding Structures | 0.001 | 0.016 | 0.002 | 0.040 | 135 | 0.5% |
| 203 | Religious Buildings | 0.000 | 0.013 | 0.000 | 0.021 | 26 | 0.1% |
| 221 | Conservation and Control Structures | 0.000 | 0.004 | 0.000 | 0.011 | 50 | 0.2% |
| 204 | Public Safety Buildings | 0.000 | 0.006 | 0.000 | 0.007 | n<10 | -- |
| 211 | Mine Shafts | 0.000 | 0.005 | 0.000 | 0.008 | 15 | 0.1% |
| 345 | Floating Oil and Gas Drilling and Production Platforms | 0.000 | 0.002 | 0.000 | 0.003 | 17 | 0.1% |
| 346 | Nuclear Fuel | 0.000 | 0.001 | 0.000 | 0.001 | 17 | 0.1% |

Note: Total number of sample firms is 27,712.

1. The full name of this category is "Ventilation, Heating, Air-Conditioning, Commercial Refrigeration, and Other General Prpose Machinery"

**TABLE 2. Fraction of variance in investment share explained by industry**
**($R^2$ from regressing investment share on 3-digit SIC industry dummy variables)**

| Asset Type Code | Description | R-Squared |
|---|---|---|
| | **Equipment** | |
| 312 | Office Equipment Except Computers and Peripherals | 0.1055 |
| 316 | Capitalized Software Purchased Separately | 0.1259 |
| 321 | Fabricated Metal Products | 0.1695 |
| 324 | Other General Purpose Machinery | 0.1849 |
| 351 | Furniture and Related Products | 0.2319 |
| 322 | Metalworking Machinery | 0.2436 |
| 315 | Medical Equipment and Supplies | 0.248 |
| 331 | Cars and Light Trucks | 0.2708 |
| 311 | Computer and Peripheral Equipment | 0.2834 |
| 343 | Electrical Equipment, NEC | 0.286 |
| 355 | Other Miscellaneous Equipment | 0.2956 |
| 361 | Artwork, Books, and Other Equipment, NEC | 0.2978 |
| 314 | Navigational, Measuring, Electromedical, and Control Instruments | 0.3012 |
| 323 | Special Industrial Machinery | 0.3114 |
| 334 | Other Transportation Equipment | 0.3455 |
| 353 | Construction Machinery | 0.3784 |
| 313 | Communications, Audio, and Video Equipment | 0.381 |
| 341 | Engine, Turbine, and Power Transmission Equipment | 0.4071 |
| 344 | Mining and Oil and Gas Field Machinery and Equipment | 0.4213 |
| 354 | Service Industry Equipment | 0.4261 |
| 352 | Agricultural Equipment | 0.4377 |
| 332 | Heavy Duty Trucks | 0.4406 |
| 342 | Electrical Transmission and Distribution Equipment | 0.4811 |
| 333 | Aerospace Products and Parts | 0.5644 |
| 345 | Floating Oil and Gas Drilling and Production Platforms | 0.6784 |

**TABLE 2 continued…**
**Structures**

| | | |
|---|---|---|
| 181 | Air, Land, and Water Transportation Facilities | 0.0712 |
| 142 | Medical Offices | 0.2375 |
| 203 | Religious Buildings | 0.2614 |
| 162 | Special Care Facilities | 0.2851 |
| 151 | Automotive Facilities | 0.287 |
| 223 | Other Non-building Structures, NEC | 0.2998 |
| 211 | Mine Shafts | 0.4022 |
| 131 | Manufacturing, Processing, and Assembly Plants | 0.4121 |
| 153 | Multi-Retail Stores | 0.4378 |
| 191 | Telecommunication Facilities | 0.4915 |
| 202 | Special School and Other Educational Facilities | 0.5 |
| 154 | Warehouses and Distribution Centers (except Passenger) | 0.5108 |
| 212 | Petroleum and Natural Gas Wells | 0.511 |
| 152 | Stores - Food Related | 0.5137 |
| 161 | Hospitals | 0.5331 |
| 213 | Other Mining and Well Construction | 0.5341 |
| 155 | Other Commercial Stores/Buildings, NEC | 0.5389 |
| 171 | Amusement and Recreational Facilities | 0.549 |
| 222 | Highway and Street Structures | 0.5495 |
| 192 | Electric, Nuclear, and Other Power Facilities | 0.5603 |
| 201 | Preschool, Primary/Secondary, and Higher Education Facilities | 0.5603 |
| 141 | Office, Bank, and Professional Buildings | 0.5921 |
| 221 | Conservation and Control Structures | 0.62 |
| 132 | Industrial Nonbuilding Structures | 0.635 |
| 111 | Residential Structures | 0.6446 |
| 193 | Water Supply, Sewage, and Waste Disposal Facilities | 0.6532 |
| 112 | Manufactured (Mobile) Homes | 0.6706 |
| 121 | Hotels, Motels, and Inns | 0.6922 |
| 204 | Public Safety Buildings | 0.9408 |

**TABLE 3. Partial correlations between Computer investment share and each other type's investment share**

**(Sorted by correlation. Only those with correlations significant above the 99% level are shown. Correlations control for 3-digit industry dummies)**

| Asset Type Code | Description | Correlation |
|---|---|---|
| 141 | Office, Bank, and Professional Buildings | 0.248 |
| 314 | Navigational, Measuring, Electromedical, and Control Instruments | 0.214 |
| 351 | Furniture and Related Products | 0.104 |
| 312 | Office Equipment Except Computers and Peripherals | 0.086 |
| 316 | Capitalized Software Purchased Separately | 0.083 |
| 155 | Other Commercial Stores/Buildings, NEC | 0.072 |
| 153 | Multi-Retail Stores | 0.060 |
| 333 | Aerospace Products and Parts | 0.039 |
| 361 | Artwork, Books, and Other Equipment, NEC | 0.030 |
| 313 | Communications, Audio, and Video Equipment | -0.019 |
| 344 | Mining and Oil and Gas Field Machinery and Equipment | -0.020 |
| 332 | Heavy Duty Trucks | -0.022 |
| 355 | Other Miscellaneous Equipment | -0.024 |
| 346 | Nuclear Fuel | -0.025 |
| 213 | Other Mining and Well Construction | -0.026 |
| 342 | Electrical Transmission and Distribution Equipment | -0.028 |
| 341 | Engine, Turbine, and Power Transmission Equipment | -0.028 |
| 323 | Special Industrial Machinery | -0.028 |
| 132 | Industrial Nonbuilding Structures | -0.034 |
| 151 | Automotive Facilities | -0.035 |
| 181 | Air, Land, and Water Transportation Facilities | -0.041 |
| 192 | Electric, Nuclear, and Other Power Facilities | -0.045 |
| 322 | Metalworking Machinery | -0.050 |
| 212 | Petroleum and Natural Gas Wells | -0.057 |
| 191 | Telecommunication Facilities | -0.070 |
| 331 | Cars and Light Trucks | -0.242 |

**TABLE 4. ACES asset types and aggregated categories used in regressions**

| Original ACES Asset Type Codes | Description | Aggregated Category Names |
|---|---|---|
| **Equipment** | | |
| 311 | Computer and Peripheral Equipment | Computers |
| 312 | Office Equipment Except Computers and Peripherals | Office Equipment |
| 313 | Communications, Audio, and Video Equipment | Communications and AV Equipment |
| 314 | Navigational, Measuring, Electromedical, and Control Instruments | Instruments |
| 315 | Medical Equipment and Supplies | |
| 316 | Capitalized Software Purchased Separately | Software |
| 321 | Fabricated Metal Products | Fabricated Metal Products |
| 322 | Metalworking Machinery | Metalworking Machinery |
| 323 | Special Industrial Machinery | Special Industrial Machinery |
| 324 | Ventilation, Heating, Air-Conditioning, Commercial Refrigeration, and Other General Purpose Machinery | General Purpose Machinery |
| 331 | Cars and Light Trucks | Autos |
| 332 | Heavy Duty Trucks | Trucks |
| 333 | Aerospace Products and Parts | Aircraft |
| 334 | Other Transportation Equipment | Other Transportation Equipment |
| 341 | Engine, Turbine, and Power Transmission Equipment | Electrical Equipment |
| 342 | Electrical Transmission and Distribution Equipment | |
| 343 | Electrical Equipment, NEC | |
| 344 | Mining and Oil and Gas Field Machinery and Equipment | Miscellaneous Equipment |
| 345 | Floating Oil and Gas Drilling and Production Platforms | |
| 346 | Nuclear Fuel | |
| 351 | Furniture and Related Products | |
| 352 | Agricultural Equipment | |
| 353 | Construction Machinery | |
| 354 | Service Industry Equipment | |
| 355 | Other Miscellaneous Equipment | |
| 361 | Artwork, Books, and Other Equipment, NEC | |

| TABLE 4 continued… | | |
|---|---|---|
| **Structures** | | |
| 131 | Manufacturing, Processing, and Assembly Plants | Industrial Buildings |
| 132 | Industrial Nonbuilding Structures | |
| 141 | Office, Bank, and Professional Buildings | Offices |
| 142 | Medical Offices | |
| 151 | Automotive Facilities | Commercial Buildings |
| 152 | Stores - Food Related | |
| 153 | Multi-Retail Stores | |
| 154 | Warehouses and Distribution Centers (except Passenger) | |
| 155 | Other Commercial Stores/Buildings, NEC | |
| 161 | Hospitals | |
| 162 | Special Care Facilities | |
| 171 | Amusement and Recreational Facilities | |
| 181 | Air, Land, and Water Transportation Facilities | Utility Structures |
| 191 | Telecommunication Facilities | |
| 192 | Electric, Nuclear, and Other Power Facilities | |
| 193 | Water Supply, Sewage, and Waste Disposal Facilities | |
| 111 | Residential Structures | Other Structures |
| 112 | Manufactured (Mobile) Homes | |
| 121 | Hotels, Motels, and Inns | |
| 201 | Preschool, Primary/Secondary, and Higher Education Facilities | |
| 202 | Special School and Other Educational Facilities | |
| 203 | Religious Buildings | |
| 204 | Public Safety Buildings | |
| 211 | Mine Shafts | |
| 212 | Petroleum and Natural Gas Wells | |
| 213 | Other Mining and Well Construction | |
| 221 | Conservation and Control Structures | |
| 222 | Highway and Street Structures | |
| 223 | Other Non-building Structures, NEC | |

**Table 5 -- Production Function Regressions**

| | 1998 | | | 1999 | | | 2000 | | | 2001 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coef. Estimate | | | Coef. Estimate | | | Coef. Estimate | | | Coef. Estimate | | |
| Investment Shares: | | | | | | | | | | | | |
| Computers | 0.55 | (0.10) | *** | 0.57 | (0.11) | *** | 0.47 | (0.12) | *** | 0.47 | (0.12) | *** |
| Office Equipment | 0.15 | (0.24) | | 0.14 | (0.25) | | 0.08 | (0.28) | | 0.05 | (0.29) | |
| Communications and AV Equipment | 0.47 | (0.21) | ** | 0.81 | (0.25) | *** | 0.80 | (0.25) | *** | 0.74 | (0.30) | ** |
| Software | 0.93 | (0.22) | *** | 0.76 | (0.23) | *** | 0.63 | (0.20) | *** | 0.65 | (0.19) | *** |
| Fabricated Metal Products | -0.04 | (0.13) | | -0.06 | (0.14) | | 0.04 | (0.17) | | 0.05 | (0.17) | |
| Metalworking Machinery | 0.09 | (0.08) | | 0.03 | (0.09) | | -0.01 | (0.10) | | 0.02 | (0.09) | |
| General Purpose Machinery | 0.11 | (0.10) | | 0.13 | (0.10) | | 0.21 | (0.13) | * | 0.28 | (0.13) | ** |
| Autos | 0.40 | (0.40) | | 0.44 | (0.47) | | 0.37 | (0.39) | | 0.50 | (0.36) | |
| Trucks | -0.05 | (0.28) | | -0.16 | (0.29) | | -0.20 | (0.27) | | -0.15 | (0.27) | |
| Aircraft | -0.01 | (0.16) | | -0.33 | (0.20) | | -0.44 | (0.21) | ** | -0.21 | (0.21) | |
| Other Transportation Equipment | -0.04 | (0.22) | | -0.23 | (0.25) | | -0.18 | (0.25) | | 0.04 | (0.25) | |
| Industrial Buildings | 0.20 | (0.11) | * | 0.22 | (0.12) | * | 0.07 | (0.13) | | 0.19 | (0.13) | |
| Offices | 0.56 | (0.17) | *** | 0.49 | (0.17) | *** | 0.54 | (0.19) | *** | 0.52 | (0.20) | *** |
| Commercial Buildings | -0.02 | (0.15) | | -0.06 | (0.16) | | -0.27 | (0.16) | * | -0.19 | (0.15) | |
| Utility Structures | -0.07 | (0.15) | | -0.17 | (0.20) | | -0.02 | (0.19) | | 0.26 | (0.18) | |
| Other Structures | -0.12 | (0.16) | | 0.14 | (0.20) | | -0.14 | (0.22) | | 0.06 | (0.22) | |
| Instruments | 0.17 | (0.16) | | 0.07 | (0.18) | | -0.12 | (0.20) | | -0.11 | (0.19) | |
| Electrical Equipment | -0.15 | (0.17) | | -0.13 | (0.21) | | -0.12 | (0.21) | | 0.12 | (0.20) | |
| Miscellaneous Equipment | 0.11 | (0.10) | | 0.09 | (0.11) | | -0.04 | (0.11) | | 0.01 | (0.11) | |
| Other Variables: | | | | | | | | | | | | |
| log(emp) | 0.53 | (0.05) | *** | 0.53 | (0.05) | *** | 0.52 | (0.04) | *** | 0.49 | (0.05) | *** |
| log(k) | 0.41 | (0.02) | *** | 0.43 | (0.02) | *** | 0.45 | (0.03) | *** | 0.44 | (0.03) | *** |
| Size Class2 | -0.04 | (0.06) | | -0.10 | (0.07) | | -0.05 | (0.07) | | -0.01 | (0.07) | |
| Size Class3 | 0.02 | (0.07) | | -0.03 | (0.08) | | -0.02 | (0.08) | | 0.03 | (0.09) | |
| Size Class4 | -0.02 | (0.10) | | -0.07 | (0.10) | | -0.03 | (0.09) | | 0.04 | (0.11) | |
| Size Class5 | 0.08 | (0.14) | | -0.05 | (0.15) | | -0.07 | (0.14) | | 0.07 | (0.17) | |
| Spike dummy | 0.07 | (0.04) | ** | 0.08 | (0.04) | * | 0.06 | (0.04) | | 0.04 | (0.04) | |
| Constant | 3.62 | (0.17) | *** | 3.11 | (0.19) | *** | 3.36 | (0.22) | *** | 3.09 | (0.21) | *** |
| Number of Observations | 1448 | | | 1358 | | | 1265 | | | 1283 | | |
| R-Sq | 0.9109 | | | 0.8968 | | | 0.9004 | | | 0.9041 | | |

Robust standard errors are shown in parentheses.
*** denotes significance at the 99% level
** denotes significance at the 95% level
* denotes significance at the 90% level

**Table 6 -- Labor Productivity Regressions**

| | 1998 | 1999 | 2000 | 2001 |
|---|---|---|---|---|
| Variable | Coef. Estimate | Coef. Estimate | Coef. Estimate | Coef. Estimate |
| Investment Shares: | | | | |
| Computers | 0.54 (0.10) *** | 0.57 (0.11) *** | 0.47 (0.12) *** | 0.47 (0.12) *** |
| Office Equipment | 0.13 (0.23) | 0.13 (0.25) | 0.08 (0.28) | 0.04 (0.29) |
| Communications and AV Equipment | 0.45 (0.22) ** | 0.80 (0.25) *** | 0.79 (0.25) *** | 0.74 (0.32) ** |
| Software | 0.93 (0.22) *** | 0.75 (0.23) *** | 0.63 (0.20) *** | 0.64 (0.20) *** |
| Fabricated Metal Products | -0.03 (0.13) | -0.06 (0.14) | 0.04 (0.17) | 0.04 (0.17) |
| Metalworking Machinery | 0.08 (0.08) | 0.03 (0.09) | -0.01 (0.10) | 0.02 (0.09) |
| General Purpose Machinery | 0.10 (0.10) | 0.14 (0.10) | 0.21 (0.13) * | 0.27 (0.13) ** |
| Autos | 0.37 (0.40) | 0.43 (0.47) | 0.35 (0.38) | 0.44 (0.36) |
| Trucks | -0.05 (0.27) | -0.16 (0.29) | -0.21 (0.27) | -0.14 (0.26) |
| Aircraft | -0.05 (0.14) | -0.34 (0.20) * | -0.44 (0.21) ** | -0.25 (0.22) |
| Other Transportation Equipment | -0.04 (0.21) | -0.23 (0.25) | -0.19 (0.25) | 0.03 (0.24) |
| Industrial Buildings | 0.19 (0.11) * | 0.21 (0.12) * | 0.07 (0.13) | 0.17 (0.13) |
| Offices | 0.57 (0.17) *** | 0.50 (0.17) *** | 0.54 (0.19) *** | 0.51 (0.19) *** |
| Commercial Buildings | -0.03 (0.15) | -0.06 (0.16) | -0.27 (0.16) * | -0.20 (0.15) |
| Utility Structures | -0.08 (0.14) | -0.17 (0.20) | -0.02 (0.18) | 0.26 (0.18) |
| Other Structures | -0.11 (0.16) | 0.14 (0.19) | -0.14 (0.21) | 0.06 (0.22) |
| Instruments | 0.17 (0.16) | 0.08 (0.18) | -0.11 (0.20) | -0.08 (0.18) |
| Electrical Equipment | -0.17 (0.17) | -0.14 (0.21) | -0.12 (0.20) | 0.12 (0.20) |
| Miscellaneous Equipment | 0.10 (0.10) | 0.09 (0.11) | -0.04 (0.11) | 0.01 (0.10) |
| Other Variables: | | | | |
| Capital-Labor ratio | 0.41 (0.02) *** | 0.43 (0.02) *** | 0.45 (0.03) *** | 0.44 (0.03) *** |
| Size Class2 | -0.10 (0.05) * | -0.14 (0.06) ** | -0.08 (0.07) | -0.09 (0.06) |
| Size Class3 | -0.08 (0.05) | -0.09 (0.06) | -0.06 (0.07) | -0.09 (0.06) |
| Size Class4 | -0.17 (0.06) *** | -0.15 (0.06) ** | -0.10 (0.07) | -0.14 (0.06) ** |
| Size Class5 | -0.14 (0.05) *** | -0.19 (0.06) *** | -0.18 (0.06) *** | -0.22 (0.06) *** |
| Spike dummy | 0.07 (0.04) ** | 0.08 (0.04) ** | 0.06 (0.04) | 0.04 (0.04) |
| Constant | 3.67 (0.16) *** | 3.12 (0.19) *** | 3.37 (0.22) *** | 3.18 (0.20) *** |
| | | | | |
| Number of Observations | 1448 | 1358 | 1265 | 1283 |
| R-Sq | 0.6778 | 0.6427 | 0.6433 | 0.6525 |

Robust standard errors are shown in parentheses.
*** denotes significance at the 99% level
** denotes significance at the 95% level
* denotes significance at the 90% level

**Table 7 -- 2FP Regressions**

| | 1998 | | | 1999 | | | 2000 | | | 2001 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Coef. Estimate | | | Coef. Estimate | | | Coef. Estimate | | | Coef. Estimate | | |
| Investment Shares: | | | | | | | | | | | | |
| Computers | 1.01 | (0.27) | *** | 0.88 | (0.28) | *** | 0.65 | (0.31) | ** | 0.46 | (0.33) | |
| Office Equipment | 0.26 | (0.48) | | 0.28 | (0.52) | | 0.05 | (0.53) | | -0.13 | (0.54) | |
| Communications and AV Equipment | 0.73 | (0.49) | | 1.19 | (0.54) | ** | 2.07 | (0.57) | *** | 1.31 | (0.43) | *** |
| Software | 1.89 | (0.55) | *** | 2.19 | (0.48) | *** | 1.64 | (0.48) | *** | 1.55 | (0.48) | *** |
| Fabricated Metal Products | -0.28 | (0.39) | | -0.58 | (0.44) | | -0.73 | (0.50) | | -0.41 | (0.47) | |
| Metalworking Machinery | 0.12 | (0.23) | | 0.02 | (0.25) | | -0.17 | (0.26) | | -0.15 | (0.27) | |
| General Purpose Machinery | 0.47 | (0.30) | | 0.24 | (0.32) | | 0.39 | (0.36) | | 0.81 | (0.33) | ** |
| Autos | 0.61 | (0.88) | | 0.42 | (1.09) | | 1.17 | (0.85) | | 1.00 | (0.94) | |
| Trucks | 0.65 | (0.76) | | 0.15 | (0.80) | | -0.18 | (0.80) | | -0.17 | (0.77) | |
| Aircraft | 0.26 | (0.72) | | 0.31 | (0.82) | | 0.22 | (0.86) | | -0.38 | (1.06) | |
| Other Transportation Equipment | 0.50 | (0.70) | | -0.53 | (0.75) | | -0.13 | (0.80) | | 0.39 | (0.76) | |
| Industrial Buildings | 0.37 | (0.35) | | 0.48 | (0.34) | | 0.07 | (0.41) | | 0.46 | (0.40) | |
| Offices | 1.03 | (0.44) | ** | 1.39 | (0.45) | *** | 1.18 | (0.52) | ** | 1.34 | (0.54) | ** |
| Commercial Buildings | 0.50 | (0.39) | | 0.28 | (0.37) | | -0.01 | (0.39) | | -0.14 | (0.38) | |
| Utility Structures | -0.34 | (0.49) | | -0.03 | (0.48) | | 0.06 | (0.58) | | 0.53 | (0.50) | |
| Other Structures | -0.84 | (0.62) | | 0.67 | (0.56) | | -0.34 | (0.70) | | 0.33 | (0.77) | |
| Instruments | 0.41 | (0.51) | | 0.06 | (0.54) | | -0.42 | (0.64) | | -0.51 | (0.58) | |
| Electrical Equipment | -0.68 | (0.50) | | -0.37 | (0.66) | | -0.61 | (0.74) | | 0.20 | (0.54) | |
| Miscellaneous Equipment | -0.03 | (0.27) | | -0.14 | (0.30) | | -0.72 | (0.33) | ** | -0.45 | (0.32) | |
| Other Variables: | | | | | | | | | | | | |
| Size Class2 | 0.56 | (0.13) | *** | 0.42 | (0.14) | *** | 0.48 | (0.14) | *** | 0.65 | (0.15) | *** |
| Size Class3 | 1.03 | (0.12) | *** | 1.08 | (0.14) | *** | 1.10 | (0.15) | *** | 1.24 | (0.15) | *** |
| Size Class4 | 1.46 | (0.13) | *** | 1.46 | (0.15) | *** | 1.54 | (0.15) | *** | 1.61 | (0.16) | *** |
| Size Class5 | 2.46 | (0.13) | *** | 2.46 | (0.14) | *** | 2.46 | (0.15) | *** | 2.51 | (0.16) | *** |
| Spike dummy | 0.07 | (0.09) | | 0.05 | (0.10) | | 0.00 | (0.11) | | 0.04 | (0.10) | |
| Constant | 3.67 | (0.40) | *** | 2.85 | (0.46) | *** | 3.82 | (0.56) | *** | 2.65 | (0.61) | *** |
| | | | | | | | | | | | | |
| Number of Observations | 1403 | | | 1309 | | | 1226 | | | 1242 | | |
| R-Sq | 0.498 | | | 0.4958 | | | 0.4754 | | | 0.4621 | | |

Robust standard errors are shown in parentheses.
*** denotes significance at the 99% level
** denotes significance at the 95% level
* denotes significance at the 90% level

**Table 8 -- 3FP Regressions**

| | 1998 | 1999 | 2000 | 2001 |
|---|---|---|---|---|
| Variable | Coef. Estimate | Coef. Estimate | Coef. Estimate | Coef. Estimate |
| Investment Shares: | | | | |
| Computers | 0.23 (0.19) | 0.34 (0.16) ** | 0.09 (0.21) | -0.14 (0.18) |
| Office Equipment | 0.75 (0.32) ** | 0.64 (0.30) ** | 0.39 (0.38) | 0.23 (0.30) |
| Communications and AV Equipment | 0.28 (0.25) | 0.50 (0.34) | 1.97 (1.20) * | 0.28 (0.43) |
| Software | 0.50 (0.31) | 0.53 (0.31) * | -0.13 (0.41) | -0.20 (0.41) |
| Fabricated Metal Products | 0.51 (0.17) *** | 0.60 (0.17) *** | 0.05 (0.23) | 0.15 (0.21) |
| Metalworking Machinery | 0.30 (0.14) ** | 0.36 (0.14) ** | -0.01 (0.15) | -0.03 (0.13) |
| General Purpose Machinery | 0.30 (0.19) | 0.37 (0.16) ** | -0.02 (0.20) | 0.04 (0.21) |
| Autos | -0.36 (0.39) | -0.08 (0.44) | -0.12 (0.61) | -0.78 (0.42) * |
| Trucks | 0.10 (0.34) | -0.17 (0.34) | -0.37 (0.39) | -0.76 (0.35) ** |
| Aircraft | -0.41 (0.48) | -0.82 (0.71) | -0.44 (0.33) | 0.12 (0.62) |
| Other Transportation Equipment | -0.45 (0.45) | -0.61 (0.48) | -0.45 (0.42) | -0.70 (0.47) |
| Industrial Buildings | 0.31 (0.19) * | 0.30 (0.17) * | 0.04 (0.22) | 0.15 (0.21) |
| Offices | 0.49 (0.34) | 0.69 (0.29) ** | 0.09 (0.39) | 0.11 (0.37) |
| Commercial Buildings | 0.25 (0.21) | 0.26 (0.16) * | -0.03 (0.20) | -0.16 (0.17) |
| Utility Structures | -0.60 (0.34) * | -0.48 (0.38) | -1.51 (1.38) | -0.12 (0.31) |
| Other Structures | -1.28 (0.84) | -0.04 (0.37) | -0.36 (0.70) | -0.21 (0.42) |
| Instruments | 0.21 (0.26) | 0.36 (0.32) | 0.31 (0.41) | -0.08 (0.34) |
| Electrical Equipment | -0.49 (0.35) | -0.32 (0.31) | -0.74 (0.60) | -0.04 (0.40) |
| Miscellaneous Equipment | 0.09 (0.18) | 0.09 (0.18) | -0.26 (0.25) | -0.16 (0.16) |
| Other Variables: | | | | |
| Size Class2 | 0.40 (0.16) ** | 0.24 (0.10) ** | 0.34 (0.15) ** | 0.49 (0.11) *** |
| Size Class3 | 0.35 (0.12) *** | 0.30 (0.09) *** | 0.38 (0.18) ** | 0.58 (0.10) *** |
| Size Class4 | 0.45 (0.15) *** | 0.38 (0.10) *** | 0.64 (0.15) *** | 0.62 (0.11) *** |
| Size Class5 | 0.60 (0.13) *** | 0.59 (0.10) *** | 0.78 (0.13) *** | 0.82 (0.11) *** |
| Spike dummy | 0.18 (0.05) *** | 0.18 (0.05) *** | -0.03 (0.10) | 0.06 (0.05) |
| Constant | 0.58 (0.23) ** | 0.26 (0.27) | 0.62 (0.37) * | 1.12 (0.31) *** |
| Number of Observations | 1394 | 1217 | 1221 | 1239 |
| R-Sq | 0.3662 | 0.3347 | 0.3012 | 0.3212 |

Robust standard errors are shown in parentheses.
*** denotes significance at the 99% level
** denotes significance at the 95% level
* denotes significance at the 90% level

**Table 9 - Regressions using pre-estimated fixed effects**

| Dependent Variable: | 1995-1997 Fixed Effect | 1999-2001 Fixed Effect | Difference in Fixed Effects (1999 2001 minus 1995-1997) |
|---|---|---|---|
| | Coef. Estimate | Coef. Estimate | Coef. Estimate |
| Investment Shares: | | | |
| Computers | 0.18 (0.07) *** | 0.24 (0.08) *** | 0.14 (0.05) ** |
| Office Equipment | 0.12 (0.18) | 0.01 (0.20) | -0.11 (0.13) |
| Communications and AV Equipment | 0.20 (0.11) * | 0.41 (0.14) *** | 0.22 (0.11) ** |
| Software | 0.49 (0.15) *** | 0.41 (0.16) *** | 0.06 (0.11) |
| Fabricated Metal Products | -0.09 (0.15) | 0.01 (0.17) | 0.06 (0.12) |
| Metalworking Machinery | 0.07 (0.08) | -0.01 (0.08) | -0.04 (0.06) |
| General Purpose Machinery | 0.21 (0.10) ** | 0.24 (0.11) ** | -0.11 (0.08) |
| Autos | 0.03 (0.21) | 0.13 (0.19) | 0.31 (0.13) ** |
| Trucks | 0.08 (0.17) | -0.08 (0.18) | 0.14 (0.14) |
| Aircraft | -0.04 (0.15) | -0.22 (0.18) | -0.13 (0.13) |
| Other Transportation Equipment | 0.03 (0.15) | -0.05 (0.17) | 0.22 (0.12) * |
| Industrial Buildings | 0.20 (0.10) * | 0.10 (0.13) | -0.01 (0.08) |
| Offices | 0.46 (0.12) *** | 0.22 (0.13) | -0.20 (0.10) ** |
| Commercial Buildings | -0.02 (0.08) | -0.09 (0.09) | 0.17 (0.06) *** |
| Utility Structures | 0.09 (0.08) | 0.13 (0.11) | 0.26 (0.07) *** |
| Other Structures | -0.01 (0.10) | 0.06 (0.12) | 0.28 (0.08) *** |
| Instruments | 0.14 (0.15) | -0.14 (0.19) | 0.05 (0.14) |
| Electrical Equipment | 0.05 (0.10) | -0.06 (0.13) | 0.10 (0.08) |
| Miscellaneous Equipment | 0.02 (0.07) | -0.02 (0.09) | 0.08 (0.06) |
| Constant | -0.11 (0.04) *** | -0.07 (0.05) | -0.07 (0.03) ** |
| Number of Observations | 1225 | 1178 | 844 |
| R-Sq | 0.1473 | 0.1319 | 0.081 |

Robust standard errors are shown in parentheses.
First-stage regressions – used to obtain productivity residuals – contain industry, state, size, and spike dummies
*** denotes significance at the 99% level
** denotes significance at the 95% level
* denotes significance at the 90% level

**Table 10 -- Production Function Regressions, Manufacturing Sector**

| | 1998 | | | 1999 | | | 2000 | | | 2001 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Coef. Estimate | | | Coef. Estimate | | | Coef. Estimate | | | Coef. Estimate | | |
| Investment Shares: | | | | | | | | | | | | |
| Computers | 0.28 | (0.14) | ** | 0.11 | (0.17) | | 0.06 | (0.19) | | 0.13 | (0.17) | |
| Office Equipment | -0.36 | (0.23) | | -0.43 | (0.31) | | -0.32 | (0.38) | | -0.37 | (0.33) | |
| Communications and AV Equipment | 0.50 | (0.31) | | 0.65 | (0.36) | * | 0.71 | (0.38) | * | 0.88 | (0.48) | * |
| Software | 0.67 | (0.23) | *** | 0.77 | (0.25) | *** | 0.58 | (0.25) | ** | 0.65 | (0.24) | *** |
| Fabricated Metal Products | 0.06 | (0.12) | | 0.06 | (0.13) | | 0.18 | (0.17) | | 0.18 | (0.16) | |
| Metalworking Machinery | 0.11 | (0.08) | | 0.00 | (0.09) | | -0.02 | (0.09) | | -0.01 | (0.09) | |
| General Purpose Machinery | 0.15 | (0.10) | | 0.18 | (0.09) | * | 0.21 | (0.11) | * | 0.26 | (0.09) | *** |
| Autos | 0.20 | (0.31) | | 0.42 | (0.33) | | 0.03 | (0.26) | | -0.13 | (0.24) | |
| Trucks | 0.32 | (0.44) | | 0.43 | (0.47) | | 0.35 | (0.57) | | 0.19 | (0.56) | |
| Aircraft | -0.07 | (0.20) | | -0.23 | (0.29) | | -0.25 | (0.30) | | -0.05 | (0.32) | |
| Other Transportation Equipment | -0.47 | (0.36) | | -0.43 | (0.51) | | -0.42 | (0.53) | | -0.18 | (0.53) | |
| Industrial Buildings | 0.13 | (0.11) | | 0.20 | (0.11) | * | 0.15 | (0.12) | | 0.20 | (0.13) | |
| Offices | 0.62 | (0.20) | *** | 0.75 | (0.23) | *** | 0.61 | (0.25) | ** | 0.40 | (0.26) | |
| Commercial Buildings | 0.65 | (0.27) | ** | 0.76 | (0.25) | *** | 0.96 | (0.24) | *** | 0.95 | (0.24) | *** |
| Utility Structures | 0.61 | (0.30) | ** | 0.42 | (0.47) | | 1.16 | (0.56) | ** | 0.95 | (0.45) | ** |
| Other Structures | 0.37 | (0.34) | | 0.97 | (0.47) | ** | 1.14 | (0.56) | ** | 0.89 | (0.42) | ** |
| Instruments | 0.37 | (0.19) | * | 0.22 | (0.18) | | 0.30 | (0.29) | | 0.20 | (0.26) | |
| Electrical Equipment | -0.08 | (0.25) | | -0.28 | (0.36) | | -0.33 | (0.37) | | -0.11 | (0.23) | |
| Miscellaneous Equipment | 0.01 | (0.13) | | 0.08 | (0.15) | | 0.01 | (0.14) | | 0.01 | (0.13) | |
| Other Variables: | | | | | | | | | | | | |
| Log(emp) | 0.67 | (0.05) | *** | 0.71 | (0.05) | *** | 0.68 | (0.05) | *** | 0.68 | (0.06) | *** |
| Log(K) | 0.34 | (0.03) | *** | 0.36 | (0.03) | *** | 0.39 | (0.03) | *** | 0.37 | (0.03) | *** |
| Size Class2 | -0.12 | (0.07) | * | -0.09 | (0.09) | | -0.08 | (0.09) | | -0.10 | (0.08) | |
| Size Class3 | -0.06 | (0.09) | | -0.06 | (0.10) | | -0.09 | (0.09) | | -0.11 | (0.10) | |
| Size Class4 | -0.14 | (0.11) | | -0.13 | (0.13) | | -0.17 | (0.12) | | -0.18 | (0.14) | |
| Size Class5 | -0.12 | (0.16) | | -0.25 | (0.18) | | -0.29 | (0.17) | * | -0.28 | (0.21) | |
| Spike dummy | 0.09 | (0.04) | ** | 0.11 | (0.05) | ** | 0.06 | (0.05) | | 0.03 | (0.05) | |
| Constant | 3 | 0 | *** | 3 | 0 | *** | 3 | 0 | *** | 4 | (0.19) | *** |
| Number of Observations | 688 | | | 636 | | | 587 | | | 588 | | |
| R-Sq | 0.9436 | | | 0.9376 | | | 0.9337 | | | 0.9419 | | |

Robust standard errors are shown in parentheses.
*** denotes significance at the 99% level
** denotes significance at the 95% level
* denotes significance at the 90% level

**Table 11 -- Production Function Regressions, Nonmanufacturing Sector**

| | 1998 | 1999 | 2000 | 2001 |
|---|---|---|---|---|
| Variable | Coef. Estimate | Coef. Estimate | Coef. Estimate | Coef. Estimate |
| Investment Shares: | | | | |
| Computers | 0.58 (0.22) *** | 0.44 (0.25) * | 0.33 (0.29) | 0.39 (0.28) |
| Office Equipment | 0.43 (0.39) | 0.25 (0.38) | 0.13 (0.44) | 0.18 (0.46) |
| Communications and AV Equipment | 0.43 (0.32) | 0.80 (0.36) ** | 0.96 (0.36) *** | 0.89 (0.36) ** |
| Software | 1.03 (0.38) *** | 0.59 (0.39) | 0.44 (0.37) | 0.50 (0.36) |
| Fabricated Metal Products | -0.41 (0.43) | -0.57 (0.58) | -0.57 (0.52) | -0.67 (0.42) |
| Metalworking Machinery | -0.38 (0.40) | -0.56 (0.46) | -0.64 (0.45) | -0.66 (0.44) |
| General Purpose Machinery | 0.12 (0.26) | 0.00 (0.30) | 0.19 (0.34) | 0.22 (0.35) |
| Autos | 0.51 (0.52) | 0.47 (0.62) | 0.41 (0.57) | 0.60 (0.52) |
| Trucks | -0.06 (0.35) | -0.25 (0.36) | -0.31 (0.36) | -0.16 (0.37) |
| Aircraft | 0.13 (0.30) | -0.37 (0.36) | -0.56 (0.41) | -0.32 (0.41) |
| Other Transportation Equipment | 0.04 (0.32) | -0.35 (0.33) | -0.30 (0.36) | -0.07 (0.36) |
| Industrial Buildings | 0.05 (0.46) | -0.40 (0.58) | -0.77 (0.59) | -0.30 (0.52) |
| Offices | 0.59 (0.28) ** | 0.23 (0.28) | 0.35 (0.35) | 0.47 (0.34) |
| Commercial Buildings | -0.12 (0.25) | -0.38 (0.27) | -0.68 (0.29) ** | -0.53 (0.29) * |
| Utility Structures | -0.17 (0.26) | -0.33 (0.31) | -0.16 (0.33) | 0.12 (0.32) |
| Other Structures | -0.32 (0.25) | -0.21 (0.29) | -0.52 (0.31) * | -0.23 (0.31) |
| Instruments | -0.33 (0.30) | -0.58 (0.40) | -0.94 (0.38) ** | -0.80 (0.37) ** |
| Electrical Equipment | -0.32 (0.31) | -0.34 (0.38) | -0.32 (0.40) | -0.12 (0.40) |
| Miscellaneous Equipment | 0.13 (0.21) | -0.03 (0.22) | -0.18 (0.25) | -0.07 (0.25) |
| Other Variables: | | | | |
| Log(emp) | 0.45 (0.06) *** | 0.45 (0.06) *** | 0.45 (0.06) *** | 0.39 (0.06) *** |
| Log(K) | 0.46 (0.03) *** | 0.47 (0.03) *** | 0.49 (0.04) *** | 0.49 (0.03) *** |
| Size Class2 | 0.07 (0.09) | -0.07 (0.11) | -0.01 (0.10) | 0.01 (0.10) |
| Size Class3 | 0.10 (0.11) | -0.03 (0.12) | -0.05 (0.11) | 0.06 (0.12) |
| Size Class4 | 0.09 (0.14) | -0.05 (0.14) | 0.01 (0.14) | 0.12 (0.15) |
| Size Class5 | 0.24 (0.20) | 0.01 (0.21) | -0.07 (0.20) | 0.17 (0.21) |
| Spike dummy | 0.06 (0.05) | 0.04 (0.06) | 0.06 (0.06) | 0.05 (0.06) |
| Constant | 3 0 *** | 3 0 *** | 4 -1 *** | 3 (0.53) *** |
| | | | | |
| Number of Observations | 773 | 735 | 690 | 707 |
| R-Sq | 0.8961 | 0.8805 | 0.8947 | 0.8976 |

Robust standard errors are shown in parentheses.
*** denotes significance at the 99% level
** denotes significance at the 95% level
* denotes significance at the 90% level